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<thead>
<tr>
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Confocal Microwave Imaging and Artifact Removal Algorithms for the Early Detection of Breast Cancer

A dissertation presented by


to

Electrical & Electronic Engineering
College of Engineering & Informatics
National University of Ireland Galway

in fulfilment of the requirements for the degree of
Doctor of Philosophy

Supervisor
Dr. Martin O’Halloran

Co-Supervisors
Dr. Edward Jones
Dr. Martin Glavin

2018
Abstract

Microwave imaging is an emerging imaging modality for the early detection of breast cancer. Early-time artifact removal and imaging algorithm are the two most important signal processing components of any Confocal Microwave Imaging (CMI) system. The artifact removal algorithm reduces the large undesired early-time reflections from the breast skin that could potentially mask the tumour response. The imaging algorithm generates images of the breast such that the tumour is a strong scatterer and clutter due to healthy breast tissues is suppressed. In this thesis, artifact removal and imaging algorithms have been investigated.

Several artifact removal algorithms for CMI along with an algorithm adapted from the Ground Penetrating Radar (GPR) have been evaluated in terms of their ability to reduce the artifact, while preserving the tumour response. The results from a comparative study have led to the development of a novel hybrid artifact removal algorithm that combines the best features of two existing artifact removal algorithms. The Hybrid Artifact Removal (HAR) algorithm has been shown to effectively reduce the early-time artifact while preserving the tumour response in 3D numerical breast phantoms. The HAR algorithm is then extended to a multistatic data acquisition approach. The proposed Multistatic Artifact Removal (MAR) algorithm has been shown to reduce the early-time artifact in selective multistatic signals, which improves the overall imaging quality compared to monostatic-only imaging.

Since different CMI prototypes use different scan configurations, the HAR algorithm, along with the Neighbourhood-based Skin Subtraction (NSS) algorithm, have been applied to the most common scan configurations used in CMI prototypes. Both algorithms have been shown to successfully reduce artifacts and produce similar quality images across all scan configurations examined. The NSS algorithm demonstrated better artifact suppression than the HAR. However, the HAR algorithm demonstrated better tumour response preservation particularly in experimental breast phantoms that were scanned with the patient-specific scan configuration of the second-generation TSAR prototype. Finally, a variety of imaging algorithms have been compared across patient data obtained from a small-scale patient study at the University of Calgary. The Delay Multiply and Sum (DMAS) imaging algorithm has been shown to provide the best quality images, with correct detection and localisation of breast lesions in most cases.
List of Publications

Book Chapters


Journal Papers


Conference Papers


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I would like to extend my thanks to friends and colleagues in the TMDLab, CAR and Biomedical research groups for their support, encouragement and good humour, which has helped me survive this journey. I am grateful to my family: my parents and my brothers and sisters for their love and support throughout this project and my life in general.

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# Contents

List of Figures ix  
List of Tables xiv  

1 Introduction 1  
1.1 Thesis Contributions ........................................ 7  
1.2 Thesis Outline ........................................ 10  

2 Literature Review 12  
2.1 Anatomy and Physiology of Breast ........................................ 12  
2.2 Breast Cancer ........................................ 14  
2.3 Dielectric Properties of Breast Tissues ........................................ 16  
2.4 Microwave Imaging ........................................ 24  
2.5 Confocal Microwave Imaging ........................................ 26  
2.5.1 Artifact Removal Algorithms ........................................ 27  
2.5.2 Imaging Algorithms ........................................ 29  
2.6 Comparative Analysis of Imaging Algorithms ........................................ 38  
2.7 Breast Phantoms ........................................ 44  
2.8 Experimental Prototypes ........................................ 46  
2.9 Conclusions ........................................ 58  

3 Artifact Removal Algorithms 60  
3.1 Introduction ........................................ 60  
3.2 Artifact Removal Algorithms ........................................ 61  
3.2.1 Average Subtraction ........................................ 62  
3.2.2 Rotation Subtraction ........................................ 62  
3.2.3 Adaptive Filtering ........................................ 63  
3.2.4 Singular Value Decomposition ........................................ 65  
3.2.5 Entropy-based Time-Window ........................................ 66  
3.2.6 Frequency Domain Pole Splitting ........................................ 67  
3.3 Simulations and Performance Metrics ........................................ 68  
3.3.1 Numerical Breast Phantoms ........................................ 69  
3.3.2 Performance Metrics ........................................ 69
## 7 Artifact Removal for Various Scan Configurations

### 7.1 Introduction

### 7.2 Artifact Removal Algorithms

#### 7.2.1 Neighbourhood-based Skin Subtraction Algorithm

### 7.3 Imaging

### 7.4 Breast Phantoms

#### 7.4.1 Numerical Breast Phantoms

### 7.5 Performance Metrics

#### 7.5.1 Signal Analysis Metrics

#### 7.5.2 Image Quality Metrics

### 7.6 Results

#### 7.6.1 Signal Analysis

#### 7.6.2 Imaging

### 7.7 Conclusions

## 8 Imaging of Patients

### 8.1 Introduction

### 8.2 Patient Scanning and Preprocessing

#### 8.2.1 Patient Information

#### 8.2.2 Patient Scanning

#### 8.2.3 Preprocessing

### 8.3 Results

### 8.4 Conclusions

## 9 Conclusions and Discussions

### 9.1 Summary of main Conclusions

### 9.2 Future Work

## References
### List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Sagittal view of the breast</td>
</tr>
<tr>
<td>2.2</td>
<td>Normal breast tissue characterisation based on percent adipose content</td>
</tr>
<tr>
<td>2.3</td>
<td>MARIA-3 antenna array with 31 wide-slot antennas (© 2010 IEEE.</td>
</tr>
<tr>
<td>2.4</td>
<td>Multistatic Array Processing for Radio-wave Imaging Acquisition (MARIA)-3</td>
</tr>
<tr>
<td>2.5</td>
<td>MARIA-4 antenna array with 60 wide-slot antennas (© 2011 IEEE.</td>
</tr>
<tr>
<td>2.6</td>
<td>MARIA-4 with antenna array and scanning hardware (© 2011 IEEE.</td>
</tr>
<tr>
<td>2.7</td>
<td>MARIA-4 with examination table and a patient (© 2016 IEEE.</td>
</tr>
<tr>
<td>2.8</td>
<td>Complete prototype at McGill University with examination table and scanning</td>
</tr>
<tr>
<td>2.9</td>
<td>Hemispherical radome and antenna elements of McGill University</td>
</tr>
<tr>
<td>2.10</td>
<td>Second generation wearable prototype at McGill University (© 2016 IEEE.</td>
</tr>
<tr>
<td>2.11</td>
<td>First generation Tissue Sensing Adaptive Radar (TSAR) prototype at the</td>
</tr>
<tr>
<td>2.12</td>
<td>Second generation Tissue Sensing Adaptive Radar (TSAR) at the University of</td>
</tr>
<tr>
<td>2.13</td>
<td>Transmission measurement prototype at the University of Calgary (© 2013</td>
</tr>
<tr>
<td>3.1</td>
<td>Finite-Difference Time Domain (FDTD) models of the breast showing the</td>
</tr>
<tr>
<td></td>
<td>permittivity at 7.5 GHz and the antenna locations shown as small cyan dots</td>
</tr>
<tr>
<td></td>
<td>on the skin: (a) homogeneous breast, (b) heterogeneous breast. The</td>
</tr>
<tr>
<td></td>
<td>corresponding beamformed images obtained after the ideal artifact</td>
</tr>
<tr>
<td></td>
<td>removal: (c) homogeneous breast, (d) heterogeneous breast.</td>
</tr>
</tbody>
</table>
3.2 The first column shows the artifact removed time-domain signals, where the solid blue line represents the ideal tumour signal obtained after ideal artifact removal and the red dotted line shows the signal obtained after the application of a real artifact removal algorithm. The second column shows images of the homogeneous breast and the third column shows the images of the heterogeneous breast obtained after the application of each artifact removal algorithm. The first row shows the results of the Rotation Subtraction algorithm. The second row shows the results of the Average Subtraction algorithm. The third row shows the results of the Wiener Filter algorithm. The fourth row shows the results of the Recursive Least Squares (RLS)-Woody combination. The fifth row shows the results of the Singular Value Decomposition (SVD) algorithm. The sixth row shows the results of the Entropy-based Time Window (EBTW) algorithm. The seventh row shows the results of the Frequency-domain pole splitting algorithm.

4.1 Three-dimensional Finite-Difference Time Domain (FDTD) breast model and antenna configuration. ......................................................... 83

4.2 Theoretical dimension $D[n]$ and time-window functions, (b,c) time-domain signals obtained after multiplying time-window functions and corresponding ideal tumour signals. ................................. 86

4.3 Time domain signals after artifact removal, (a) Multiplication with improved time-window (b) Wiener Filter over improved time-window. 87

4.4 Time domain signals before (solid lines) and after (dotted lines) artifact removal using proposed hybrid algorithm at 5 different channels: left column is early-time response (artifact) and right column is late-time response (tumour signal) (Note different amplitude ranges between early and late-time signals). .............................. 87

4.5 Coronal view of Finite-Difference Time Domain (FDTD) breast model showing permittivity of breast tissues computed at 6.0 GHz (a), and corresponding beamformed image obtained after artifact removal using hybrid algorithm (b). ......................................................... 88

5.1 Early-time part of time-domain backscattered radar signals (first 50 time samples shown). $b_{(i,j)}$ is the backscattered signal recorded at antenna $j$, where $i$ is the index of the transmitting antenna, $j$ is the index of the receiving antenna. ................................................................. 92

5.2 Early-time part of time-domain backscattered radar signals (first 50 time samples shown): (a) the monostatic signals; (b) the signals of the form $b_{(i,i+1)}$; (c) the signals of the form $b_{(i,i+2)}$; (d) and the signals of the form $b_{(i,i+3)}$. ................................................................. 94
5.3 3D FDTD model showing the breast and the antenna array. Each colour represents a tissue type. 97
5.4 Theoretical dimension $D[n]$ and estimated artifact dominant time-window functions obtained from: (a) the monostatic signals group; (b) the multistatic group containing signals of the form $b_{(i,i+1)}$; (c) the multistatic group containing signals of the form $b_{(i,i+2)}$; (d) and the multistatic group containing signals of the form $b_{(i,i+3)}$ 99
5.5 Time domain signals after artifact removal: (a) the monostatic signal $s_{(16,16)}$; (b) the multistatic signal $s_{(16,15)}$; (c) the multistatic signal $s_{(9,11)}$; (d) and the multistatic signal $s_{(3,6)}$. 100
5.6 (a) Correlation coefficient $r$ obtained by correlating $D[n]$ of monostatic signals group with $D[n]$ of multistatic signal groups ($b_{(i,i+k)}$ where $k = 1, 2, 3, 4$), (b) Signal-to-Clutter Ratio (SCR) as a function of the number of signals selected for the imaging process and the value of correlation coefficient $r$ used as threshold for signal selection. 102
5.7 Coronal view of FDTD breast models (a,d,g) showing permittivity of the breast tissues computed at the centre frequency of the pulse, corresponding monostatic beamformed images (b,e,h), and corresponding combined monostatic and multistatic (CMM) images (c,f,i). 103
5.8 Coronal view of FDTD breast models (a,d) showing permittivity of the breast tissues computed at the centre frequency of the pulse, corresponding monostatic beamformed images (b,e), and corresponding combined monostatic and multistatic (CMM) images (c,f). 104
5.9 (a) Coronal view of FDTD breast model (M6) showing permittivity of the breast tissues computed at the centre frequency of the pulse, (b) corresponding monostatic beamformed image, (c) and corresponding combined monostatic and multistatic (CMM) image. 104
6.1 An example of an internal structure configuration attached to a polycarbonate disk (right) to be placed inside a skin layer (left). Two possible tumours attached to polycarbonate rods are shown below (© 2015 IEEE. Reprinted, from [146]). 109
6.2 Dielectric properties of breast phantom material (BPM) used in development of experimental breast phantoms. The dry skin [120], high-property glandular, low-property glandular and fatty tissue [84] dielectric properties included for comparison (© 2015 IEEE. Reprinted, from [146]). 111
6.3 Computer generated model of the experimental breast phantom with glandular inclusion (© 2015 IEEE. Reprinted, from [146]). 112
List of Figures

6.4 Illustration of breast model suspended in measurement tank of Tissue Sensing Adaptive Radar (TSAR) prototype (© 2015 IEEE. Reprinted, from [146]). .......................... 112

6.5 The backscattered time-domain signal recorded at Channel 8: the corresponding ideal tumour response; and the corresponding Hybrid Artifact Removal (HAR) processed signal. .......................... 115

6.6 Time-domain signals at a number of channels after application of the Hybrid Artifact Removal (HAR) algorithm, (a) Signal at Channel 2, (b) Signal at Channel 27, (c) Signal at Channel 68, (d) Signal at Channel 96. ........................................... 116

6.7 Beamformed image of numerical phantom after artifact removal using Hybrid Artifact Removal (HAR). .................................................. 117

6.8 Beamformed images of the experimental phantoms after artifact removal using the Hybrid Artifact Removal (HAR) algorithm, (a) with tumour, (b) with tumour and gland. ........................................... 118

7.1 Time-domain backscattered signal recorded at Channel 9 and the corresponding artifact-dominant time-window ........................................ 125

7.2 Large breast phantom and scan patterns, (a) Cylindrical, (b) Hemispherical, (c) Patient-specific, (d) Orientation of antenna corresponding to fourth position of hemispherical scan pattern (© 2015 IEEE. Reprinted, from [176]) ........................................ 127

7.3 Small breast phantom and scan patterns, (a) Cylindrical, (b) Hemispherical, (c) Patient-specific (© 2015 IEEE. Reprinted, from [176]) ........................................ 128

7.4 Heterogeneous breast phantom derived from a Magnetic Resonance Imaging (MRI) scan of a patient showing distribution of different breast tissues with (a) and (b) showing side view, (c) showing top view and (d) showing bottom view. Three different types of glandular tissues are shown in different colours (© 2015 IEEE. Reprinted, from [176]). ........................................ 129

7.5 The mean Artifact Suppression Ratio (ASR) of each breast phantom is shown. The ASR is computed for each radar signal (after processing through both HAR NSS) and averaged across each breast phantom. Lower value indicates better artifact suppression. ........................................ 134

7.6 The mean Tumour and Clutter Suppression Ratio (TCSR) of each breast phantom is shown. The TCSR is computed for each radar signal (after processing through both HAR and NSS) averaged across each breast phantom. Lower values indicate better clutter suppression but also greater tumour suppression. ........................................ 135
7.7 The mean Tumour Energy Preservation Ratio (TEPR) of each breast phantom. The TEPR is computed for each radar signal (after processing through both HAR and NSS) and averaged across each breast phantom. 136

7.8 Beamformed image of C1 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm. 138

7.9 Beamformed image of H2 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm. 141

7.10 Beamformed image of P2 following artifact removal using: (a) HAR algorithm, (b) NSS algorithm. 143

7.11 Beamformed image of E2 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm. 145

7.12 Beamformed image of C3 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm. 146

7.13 Beamformed image of H3 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm. 147

7.14 Beamformed image of P3 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm. 148

8.1 Magnetic Resonance Imaging (MRI) scan of Patient 1 (© 2013 IEEE. Reprinted, from [145]). (a) Saggital view, (b) Coronal view. 158

8.2 Microwave images of Patient 1 for a range of different imaging algorithms. 159

8.2 Microwave images of Patient 1 for a range of different imaging algorithms. 160

8.2 Microwave images of Patient 1 for a range of different imaging algorithms. 161

8.3 Mammogram of Patient 2 (© 2013 IEEE. Reprinted, from [145]). 163

8.4 Microwave images of Patient 2 for a range of different imaging algorithms. 164

8.4 Microwave images of Patient 2 for a range of different imaging algorithms. 165

8.4 Microwave images of Patient 2 for a range of different imaging algorithms. 166

8.5 Magnetic Resonance Imaging (MRI) scan of Patient 3 (© 2013 IEEE. Reprinted, from [145]). 168

8.6 Microwave images of Patient 3 for a range of different algorithms. 169

8.6 Microwave images of Patient 3 for a range of different algorithms. 170

8.6 Microwave images of Patient 3 for a range of different algorithms. 171

8.7 Microwave images of Patient 4 for a range of different algorithms. 174
List of Figures

8.7  Microwave images of Patient 4 for a range of different algorithms. . 175
8.7  Microwave images of Patient 4 for a range of different algorithms. . 176
8.8  Microwave images of Patient 5 for a range of different algorithms. . 179
8.8  Microwave images of Patient 5 for a range of different algorithms. . 180
8.8  Microwave images of Patient 5 for a range of different algorithms. . 181
## List of Tables

2.1 The Breast Imaging Reporting and Data System (BI-RADS) system; Breast classes based on breast density ........................................ 14

2.2 Classification of numerical breast phantoms in the University of Wisconsin Cross-Disciplinary Electromagnetics (UWCEM) repository ......................................................... 44

2.3 Tissue types and the corresponding media numbers ........................................ 45

2.4 Single-pole Debye parameters for the different tissue types (valid for 3-10 GHz) (© 2008 IEEE. Reprinted, from [121]). ........................................ 46

3.1 Performance metrics for artifact removed signals ........................................ 72

3.2 Performance metrics for beamformed images ........................................ 72

4.1 Performance metrics for the raw signals and the beamformed images. A lower value of the Peak-to-Peak Response Ratio (PPRR) indicates a better artifact suppression. A higher value of the Tumour-to-Artifact Ratio (TAR) indicates better tumour response preservation. Higher Signal-to-Mean Ratio (SMR) and the Signal-to-Clutter Ratio (SCR) indicate better image quality ........................................ 89

5.1 Description of Breast Models ........................................ 98

5.2 Performance metrics for the raw signals and the beamformed images ...................... 105

6.1 Chosen Carbon-based mixtures for various soft tissues found in the breast (© 2015 IEEE. Reprinted, from [146]). ........................................ 110

6.2 Performance metrics for the signals and the images ........................................ 119

7.1 Summary of numerical and experimental breast phantoms used in this study .......................... 130

7.2 Debye Parameters for Numerical Breast Phantoms(© 2015 IEEE. Reprinted, from [176]) ........................................ 131

7.3 Imaging performance metrics for phantoms scanned with the cylindrical scan pattern ........................................ 139

7.4 Imaging performance metrics for phantoms scanned with hemispherical scan pattern ........................................ 142
### List of Tables

<table>
<thead>
<tr>
<th>Table No.</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.5</td>
<td>Imaging performance metrics for phantoms scanned with a patient-specific scan pattern</td>
<td>144</td>
</tr>
<tr>
<td>7.6</td>
<td>Imaging performance metrics for experimental phantoms</td>
<td>144</td>
</tr>
<tr>
<td>7.7</td>
<td>Summary of imaging performance metrics for both simulated and experimental phantoms</td>
<td>149</td>
</tr>
<tr>
<td>8.1</td>
<td>Summary of patient information [from [145]]</td>
<td>155</td>
</tr>
<tr>
<td>8.2</td>
<td>Summary of the analysis of Patient 1 microwave images</td>
<td>162</td>
</tr>
<tr>
<td>8.3</td>
<td>Summary of the analysis of Patient 2 microwave images</td>
<td>167</td>
</tr>
<tr>
<td>8.4</td>
<td>Summary of the analysis of Patient 3 microwave images</td>
<td>172</td>
</tr>
<tr>
<td>8.5</td>
<td>Summary of the analysis of Patient 4 microwave images</td>
<td>177</td>
</tr>
<tr>
<td>8.6</td>
<td>Summary of the analysis of Patient 5 microwave images</td>
<td>182</td>
</tr>
</tbody>
</table>
Glossary

2D  two-dimensional. 30, 34, 40, 41, 61, 79, 80, 82, 116

3D  three-dimensional. 3, 80, 82, 83, 85, 92, 97, 113, 119

ABS  Acrylonitrile Butadiene Styrene. 50

ACR  American College of Radiology. 14

APES  Amplitude and Phase Estimation. 37, 38

ASR  Artifact Suppression Ratio. 129, 130, 133, 135, 136, 139

BAVA-D  Balanced Antipodal Vivaldi Antenna with Director. 55, 108, 109, 112, 119, 153, 154, 177, 178

BI-RADS  Breast Imaging Reporting and Data System. 14

BPM  breast phantom material. 110

CF  Coherence Factor. 33

CF-DAS  Coherence Factor based DAS. 33, 41, 101, 105, 151, 152, 155, 156, 158, 163, 165, 172, 180

CIS  Carcinoma in-situ. 15

CM  Correlation Measure. 69, 72

CMI  Confocal Microwave Imaging. 4, 5, 7, 8, 10, 12, 25, 27, 30, 31, 58, 60, 70, 150, 152, 173, 181, 183

CMM  combined monostatic and multistatic. 92, 101, 104, 106, 177, 181

CR-DAS  Channel Ranked DAS. 33, 41, 151, 152, 155, 158, 159, 161, 163, 165, 168, 170, 172, 180

DA  Data Adaptive. 6, 10, 29, 33, 35, 40, 59, 150, 152, 172, 179
Glossary

DAS  Delay-And-Sum. 30 33 37 41 88 89 116 125 151 152 155 156 158 163 165 172 176 180

DCIS  Ductal Carcinoma *In-situ*. 15

DI  Data-Independent. 6 10 29 35 37 39 41 59 150 152 179

DMAS  Delay-Multiply-And-Sum. 32 39 42 151 152 155 156 158 163 165 173 180 181

EBTW  Entropy-based Time Window. 28 66 71 72 76 81 86 89 175 176 177 179

FDTD  Finite-Difference Time Domain. 25 46 69 83 84 97 107 109 119 129 177 179

FWHM  Full-width Half Maximum. 113 114 128 131 136 138 140 142 144 156 180

GLRT  Generalised Likelihood Ratio Test. 35 41 43

GPR  Ground Penetrating Radar. 8 10 31 61 62 65 77 175

HAR  Hybrid Artifact Removal. 8 10 89 91 93 95 96 106 108 113 121 133 142 144 148 175 179 181

IDAS  Improved Delay-And-Sum. 32 33 39 40 151 152 155 156 158 163 165 172 180

IDC  Invasive Ductal Carcinoma. 15 163 166

IF  Intermediate Frequency. 112 154

IFFT  Inverse Fourier Transform. 47 68

ILC  Invasive Lobular Carcinoma. 15

LCIS  Lobular Carcinoma *In-situ*. 15

MAMI  Multistatic Adaptive Microwave Imaging. 37 39

MAR  Multistatic Artifact Removal. 91 92 96 98 176 177 181

MARIA  Multistatic Array Processing for Radio-wave Imaging Acquisition. 46 48 50
MIST  Microwave Imaging via Space-Time. 34 37 38 40 42

MR  Magenetic Resonance. 40 41 44 45 156

MRI  Magnetic Resonance Imaging. 3 7 8 10 14 44 46 58 61 69 82 97 122 128 133 142 146 153 156 163 166 172 173 176 179

NSS  Neighbourhood-based Skin Subtraction. 9 10 121 123 133 142 144 145 147 148 155 178 180

NUIG  National University of Ireland Galway. 181

PDF  Probability Density Function. 66 81

PET  Positron Emission Tomography. 3

PPRR  Peak-to-Peak Response Ratio. 69 72 84 88 97 105 113 115 118 177

QF  Quality Factor. 32 33

RCB  Robust Capon Beamformer. 33 36 38 41 151 152 155 158 159 161 162 163 165 168 170 172 180

RLS  Recursive Least Squares. 28 64 71 72 76

RWCB  Robust Weighted Capon Beamformer. 37

SCB  Standard Capon Beamformer. 35 37

SCR  Signal-to-Clutter Ratio. 84 85 88 89 95 98 101 103 105 106 113 118 131 136 138 140 142 144 148 177

SMR  Signal-to-Mean Ratio. 69 71 72 84 85 88 89 98 101 105 106 113 114 118 132 136 138 140 142 144 148 156 158 161 163 166 168 171 172 177 180

SOI  signal of interest. 35

SSIM  Structure Similarity Index Metrics. 69 71 72 85

SVD  Singular Value Decomposition. 62 65 68 71 72 76 77 175

TAR  Tumour-to-Artifact Ratio. 84 85 88

TCSR  Tumour and Clutter Suppression Ratio. 130 134 136 144
Glossary

**TDOA**  Time-Difference-of-Arrival. 41

**TEPR**  Tumour Energy Preservation Ratio. 130, 131, 134, 136

**TMDLab**  Translational Medical Device Lab. 181

**TSAR**  Tissue Sensing Adaptive Radar. 54, 57, 108, 119, 121, 126, 152, 153, 172, 177, 179

**TWTLTA**  Travelling-Wave Tapered and Loaded Transmission-line. 52, 108

**UWB**  Ultra-Wideband Radar. 4, 26, 34, 54, 153

**UWCEM**  University of Wisconsin Cross-Disciplinary Electromagnetics. 44, 69, 97, 175, 176

**VNA**  Vector Network Analyser. 47, 51, 55, 154, 155

**WCB**  Weighted Capon Beamformer. 37, 42
Introduction

Breast cancer is one of the most common cancers to affect women worldwide. Approximately 1.7 million new cases of breast cancer were diagnosed worldwide in 2012, resulting in half a million deaths [1]. In the United States, breast cancer is the most prevalent cancer. It accounts for 29% of new cancer cases and is second only to lung cancer as the leading cause of deaths in American women. More than 246,660 new cases of breast cancer are estimated to be diagnosed in the United States this year, leading to approximately 40,000 deaths [2]. In Europe, these figures translate to 425,000 new cases and 129,000 deaths every year [3].

In Ireland, more than 2700 new cases of breast cancer are diagnosed each year. A total of 649 deaths from breast cancer were reported in 2010, making it the second largest cause of female cancer deaths in Ireland [4]. The female breast cancer mortality rate has declined over the years in Ireland, as well as other developed countries [2]. However, Ireland still has third highest mortality rate when compared to other European countries [4].

Early detection and intervention are considered to be the most important factors in improving survival rates, as treatment is likely to be more effective when cancer is diagnosed and treated in the early stages. A recent large scale study of nearly 174,000 patients observed a five-year survival rate of 96% for patients whose cancer was diagnosed at an early-stage [5]. Recent breast cancer statistics from Ireland
Introduce

1. Introduction

indicate that the survival rate of patients diagnosed early with breast cancer between 2004 and 2008 was consistently above 85% [4]. A number of studies have associated the decline in mortality rates with national breast cancer screening programmes [6], [7] that allow for detection and treatment of cancer at a curable stage.

X-ray mammography is the primary breast imaging modality used for the early-stage detection of the breast cancer. However, the limitations of X-ray mammography in terms of specificity and sensitivity are well known. In the US, 20% of all cancers are missed by conventional mammography, 75% of the identified malignancies are later found to be benign [8] and 25% of cancers are overdiagnosed (never progressing or regressing cancer) [9]. Sensitivity is even lower in younger women [8], [10]. The breast tissue in younger women typically has higher dense-to-fatty tissue ratio and malignancies occurring in dense-tissue are obscured and are statistically more likely to be missed by X-ray mammography [10].

Similarly false-positive conclusions result in unnecessary biopsies, considerable distress to the patients and an unnecessary financial burden on the health services [11]. False-negative mammograms on the other hand tend to give a false sense of security to patients, which can delay the treatment of cancer, often to the point where treatment is no longer effective. Furthermore, uncomfortable breast compression during mammography has been reported to cause mild to moderate pain [12]. The pain and discomfort of X-ray mammography could dissuade women from re-attending screening [13]. Finally, the ionising radiation of the low-energy X-rays may be particular unsafe for younger women in particular, and women with genetic susceptibility to radiation induced cancers [14].

Digital mammography has been found to be more effective in terms of detection rate (i.e. up to 28% higher) than conventional mammography in women under the age of 50, premenopausal and perimenopausal women, and in women with dense breasts [15]. However, even digital mammography does not seem to have improved the number of cancers missed by X-ray mammography [16]. Uncomfortable breast compression also remains the same between conventional and digital mammography. However, a significantly lower radiation dose is an added advantage of digital
mammography [17]. More recently, digital breast tomosynthesis or three-dimensional (3D) mammography has been developed and its diagnostic accuracy is currently being investigated [18]. An initial observational study indicates a 35% increase in the cancer detection rate (4.0 to 5.4 per 1000, \( P=0.18 \)) and an 11% decrease in follow up biopsies (15.2 to 13.5 per 1000, \( P=0.59 \)) [18], [19].

Ultrasound imaging or breast sonography are typically used as an adjunct tool to X-ray mammography. Sonography is particularly useful for the classification of breast lesions that are difficult to interpret on mammograms. Sonography also significantly improves cancer detection in high-risk women and women with dense breasts when it is used in conjunction with X-ray mammography [20], [21]. However, sonography is not used for the breast cancer screening due to its unacceptably high false-positive and false-negative rates in asymptotic women [22].

Magnetic Resonance Imaging (MRI) for breast cancer screening may be used for women who have a high risk of developing breast cancer or women with the dense breasts. However, MRI is primarily used for specific diagnostic purposes such as: to further evaluate breast abnormalities detected by the mammography; to detect small tumours (e.g. cancer cells present in under arm lymph nodes) that can not be felt or detected by ultrasound or X-ray mammography; to establish the size and the precise location of tumour(s); and to monitor the treatments (e.g. chemotherapy).

Despite the fact that the MRI has much higher overall sensitivity than either sonography or X-ray mammography, it has several limitations including: lower specificity; lower sensitivity to the ductal carcinoma in situ; longer scan times; higher costs; and limited availability [23].

Other complementary imaging modalities include Positron Emission Tomography (PET) breast thermography, electrical impedance based imaging, optical imaging and the molecular breast imaging [24]. Due to the fact that none of the existing imaging modalities has been proven to be sufficient for all aspects of breast cancer management, there is a pressing need for the development of new complementary modalities for the early detection and diagnosis of the breast cancer. [24].
Microwave imaging is a promising complementary imaging modality for the early detection of the breast cancer. The physical basis of microwave imaging is the dielectric contrast between healthy and cancerous breast tissues at microwave frequencies \[25\]. Microwave imaging can potentially be used for monitoring neoadjuvant chemotherapy treatment \[26\], breast health monitoring \[27\], and for routine screening and diagnosis of breast cancer \[28\]. The non-invasive and the non-ionising characteristics of microwaves should allow for frequent scanning of the breast using microwave imaging. In addition to safety \[29\], \[30\], microwave imaging does not require uncomfortable breast compression and it is potentially a low cost modality.

Microwave Tomography and Ultra-Wideband Radar (UWB) radar are the two main modalities of microwave imaging \[31\]. In both, the breast is illuminated with low power microwave signals by an array of antennas and backscattered signals are measured by the same array.

In microwave tomography, the backscattered signals are used for the quantitative reconstruction of the dielectric profile of the breast using inverse scattering algorithms \[32\], \[33\]. UWB radar-based imaging uses the Confocal Microwave Imaging (CMI) approach to combine the backscattered signals to locate regions of dielectric scatterings within the breast. These regions of high dielectric scatterings correspond to the tumour locations, as tumours are expected to have significantly higher microwave scattering cross sections compared to the normal breast tissues due to higher dielectric contrast.

Two approaches are commonly used for microwave signal acquisition in a CMI system. In the monostatic approach, the transmitting antenna is also used for recording the backscattered signal. In the multistatic approach, each antenna in the antenna array takes turn transmitting the UWB pulse, while all antennas in the array are used to record the backscattered signals. The multistatic approach increases the total number of backscattered signals that propagate through different paths, and hence carry more information about any scatterer within the breast, when compared to the monostatic approach. CMI is the primary focus of this thesis.
1. Introduction

The two critical signal processing challenges in most CMI systems for breast cancer detection are the early-time artifact removal and high quality image reconstruction with minimal clutter [31]. The early-time artifact consists of the input signal; reflections from the skin surface and skin-fat interface; and any antenna reverberations present. This artifact is typically several orders of magnitude greater than reflections from any tumours present within the breast. If the artifact is not removed effectively, it could easily mask tumours present within the breast at the image reconstruction stage.

Many artifact removal algorithms ranging from simple average subtraction to more complex filter-based approaches have been reported in the literature [34]–[38]. All of these algorithms have shown promising results in specific scenarios but they are based on simplifying assumptions about the degree of commonality in the artifact across all channels. However, several real-world clinical scenarios could result in greater variation in the early-stage artifact, making the artifact removal process much more difficult.

Moreover, since most of the existing artifact removal algorithms have been used to remove artifacts from mono-static radar signals, multi-static artifact removal algorithms remain to be investigated. In addition, a number of prototypes for microwave imaging have been developed. Each of these prototypes may use different arrangements of antenna elements, producing different scan patterns. Different scan pattern can impact the performance of the artifact removal algorithm. Despite the importance of the early-time artifact removal algorithm, no comprehensive study on the performance of various artifact removal algorithms has been previously reported.

Another important component of CMI is the image reconstruction. Beamforming algorithms are typically used to construct the energy profile of breast [39]–[41]. Regions of high energy within the resultant images may suggest the presence of cancerous tissue due to the dielectric contrast that exists between normal and cancerous tissue. However, the suppression of clutter due to heterogeneity of healthy breast tissues while retaining the tumour response is a challenge for the imaging algorithm. In addition, the residual early-time artifact can also impact the
1. **Introduction**

performance of the imaging algorithm, though these artifacts are often compensated by the imaging algorithm through incoherent addition. A recently reported dielectric contrast (as low as 10%) [42] between the fibroglandular and the tumour tissues is much smaller than the previously reported contrast of 500% [43], [44]. This limited contrast between healthy and tumour tissue adds an additional challenge for the imaging algorithm.

Several beamforming algorithms have been proposed to improve the tumour response while suppressing the clutter due to the heterogeneity of breast tissues. **Data-Independent (DI)** beamforming algorithms are based on the principle of coherent addition of the backscattered radar signals [35], [39], [40], [45]–[50]. Adaptive beamforming is typically used to compensate for frequency-dependent propagation effects prior to coherent addition [51]–[54]. **Data Adaptive (DA)** beamformers provide high resolution images with good clutter suppression but are computationally intensive, sensitive to steering vector inaccuracies, and are particularly susceptible to pre-processing errors [48].

The performance of beamforming algorithms has often been evaluated in the literature using: a selective set of beamforming algorithms [48], anatomically and dielectrically inaccurate numerical phantoms [51], [55], [56], and an idealised artifact removal algorithm while ignoring the impact of realistic artifact removal [54], [57], [58]. However, one recent study applied multiple imaging algorithms to clinical data from healthy volunteers [59]. The participating volunteers had no breast cancer present and therefore tumour responses were artificially introduced in the acquired data. Differential signals with induced tumour responses were used for imaging. The “clean” differential signals with no clutter from residual artifacts, healthy tissues and experimental noise may be an oversimplification of the realistic clinical scenario where the tumour signal is often embedded in the early-time artifact due to skin reflections as well as clutter. Therefore, further investigation of the performance of the imaging algorithms is required in more realistic scenarios. The current literature lacks a comprehensive evaluation of a variety of imaging algorithms in realistic experimental and clinical scenarios.
1. Introduction

Considering the above critical literature gaps identified in the area of CMI, the overall objectives of this thesis are to develop an effective artifact removal algorithm and investigate imaging algorithms that can provide good imaging quality in realistic clinical environments.

The overall objective is achieved incrementally, starting with an investigation of the artifact removal and imaging algorithms using MRI-derived numerical breast models, and then progressing to experimental breast phantoms and finally patient data. Firstly various early-time artifact removal algorithms are investigated and a novel artifact removal algorithm is developed. The efficacy of the developed algorithm in removing the early-time artifact while preserving the tumour response is demonstrated. The algorithm is applied to both monostatic, and a comparatively more challenging scenario of multistatic, signals.

Furthermore, the robustness of the developed early-time artifact removal algorithm to realistic antenna effects and experimental noise is demonstrated. The experimental data is obtained from experimental breast phantoms scanned with a clinical breast imaging prototype (namely Tissue Sensing Adaptive Radar (TSAR) [60]). The artifact removal algorithms are evaluated for various prototype scan configurations including: cylindrical; hemispherical; and an adaptive/patient-specific scan configuration used in clinical prototypes reported in [61], [47] and [60] respectively. Finally, a number of imaging algorithms developed for CMI are evaluated using experimental and real clinical data obtained from scanning patients using the TSAR prototype [61] at the University of Calgary.

The specific objectives and the thesis contributions are described in the following section.

1.1 Thesis Contributions

The specific contributions of this thesis in the area of CMI for the early detection of breast cancer are:
1. Introduction

- A number of early-time artifact removal algorithms along with algorithms adapted from Ground Penetrating Radar (GPR) applications are implemented and compared. The algorithms are applied to MRI-derived breast phantoms and the results are evaluated across a range of performance metrics. The relative advantages and disadvantages of each algorithm are identified, and the potential for improvement in the individual or combined performance is explored.


- A novel hybrid artifact removal algorithm is proposed that combines the best features of two existing artifact removal algorithms to effectively remove the artifact while preserving the tumour response. The efficacy of the algorithm is demonstrated by applying the algorithm to monostatic microwave signals acquired from 3D MRI-derived anatomically and dielectrically accurate breast phantoms. The results are analysed using a number of signal and image performance metrics.


- The Hybrid Artifact Removal (HAR) algorithm is extended for the more challenging scenario of multistatic signals and the Multistatic Artifact Removal (MAR) algorithm is proposed. Both the HAR-processed monostatic signals and MAR-processed multistatic signals are combined to produce CMI images of breast models. The combined multistatic and monostatic imaging approach is shown to improve the quality of images compared to monostatic imaging. The improvement is demonstrated using various MRI-derived breast phantoms having different radiographic breast densities and the results are evaluated.
across a range of image quality metrics.


- The robustness of the HAR algorithm is evaluated against realistic antenna effects and experimental noise. The experimental breast phantoms used in this evaluation were created using materials with dielectric properties close to that of the human breast tissue. The breast skin, the interior tissues (such as healthy fibroglandular tissues) and tumour tissues, are created using 3D moulds. The breast phantoms are scanned with the TSAR prototype developed for clinical testing. The HAR algorithm is applied to the measured microwave signals and images are created. The results are assessed using several performance metrics.

- Two promising early-time artifact removal algorithms (the HAR and the Neighbourhood-based Skin Subtraction (NSS) algorithm) are applied to breast phantoms scanned with different scan configurations. The antenna elements in the antenna array are arranged differently to produce different scan patterns. The scan patterns are chosen based on the three most common scan configurations reported in the literature. Experimental phantoms are also used in this evaluation study. The various scan configurations allow for the evaluation of the robustness of the artifact removal algorithms across various configurations and also allow for the generalisability of results across most microwave breast imaging prototype systems. Several signal analysis and image quality metrics are used to quantify and compare the results obtained from both algorithms.

Finally, the performance of a variety of DI and DA imaging algorithms reported in the literature is evaluated using patient data. The patient data is obtained from a small scale patient study conducted at University of Calgary, Canada. The various imaging algorithms are applied to the patient data post artifact removal. The resultant image quality is then compared across various algorithms using appropriate image quality metrics.

**Publication:** “Image reconstruction algorithms for confocal microwave imaging: Application to patient data”, Computerized Medical Imaging and Graphics. [To be submitted]

### 1.2 Thesis Outline

The remainder of the thesis is structured as follows: Chapter 2 describes the breast anatomy, physiology and breast cancer; a brief review of the dielectric properties of the breast; and a literature review of CMI algorithms, prototypes and clinical studies. Chapter 3 details various existing artifact removal algorithms developed for CMI and algorithms adapted from GPR and follows on to compare the relative performance of each algorithm. Chapter 4 proposes a novel hybrid artifact removal algorithm and evaluates the performance of the HAR algorithm using anatomically and dielectrically accurate breast phantoms. Chapter 5 extends the monostatic hybrid artifact removal algorithm to the more complex scenario of multistatic signals, and demonstrates improvements in the image quality achieved using the combined monostatic and multistatic imaging approach. The efficacy of the proposed approach is demonstrated using MRI-derived breast phantoms of varying radiographic density. Chapter 6 compares the robustness of the HAR algorithm to realistic antenna effects and experimental noise using experimental breast phantoms scanned with the clinical TSAR prototype. Chapter 7 evaluates the performance of the two most promising artifact removal algorithms (the HAR and the NSS algorithms) across various prototype scan configurations. Chapter 8 evaluates the relative performance of the various imaging algorithms using experimental and patient
Finally, Chapter 9 discusses the conclusions and suggestions for future work.
In this chapter, an overview of the anatomy and physiology of the breast is presented. The various types of breast cancer are described, followed by a review of various studies on the dielectric properties of cancerous and normal breast tissues. Microwave imaging for the early-stage detection of the breast cancer is introduced and the various existing artifact removal and imaging algorithms developed for CMI of the breast are described. Additionally, the most common numerical breast phantoms developed for the evaluation of microwave imaging algorithms are presented. Finally, studies examining the performance of microwave breast imaging algorithms and the clinical and experimental prototypes developed for the CMI are also reviewed.

2.1 Anatomy and Physiology of Breast

A female breast is mainly composed of fatty (adipose), glandular and fibrous tissues. Figure 2.1 shows the anatomy of a breast in the sagittal view. Glandular tissues of the breast branch out from the breast nipple in the form of 15 to 20 lobes. Each lobe is composed of several small lobules that produce milk. The clusters of alveoli within each lobule contain lactocytes (mammary secretory epithelial cells) that synthesise milk. The milk from alveoli is carried by tiny tubes called ducts toward the darker
area of the skin in the centre of the breast called areola. These smaller ducts eventually merge into one larger milk duct for each lobe that end at the nipple [62].

Fibrous or connective tissues, fat and ligaments fill the space around the lobules and the ducts. These fibrous tissues give the structural support to the breast and hold the glandular tissues in place. The supportive tissues surrounding the glands are also referred to as “stroma”. The fibrous and the glandular tissues are together referred as fibroglandular tissues. Adipose tissues (or fat) along with the fibrous tissues, surrounds the breast giving the breast shape and size along with the fibrous tissues. Muscle tissue lies underneath the breast and separates the breast from the ribs. In addition, the breast also has a network of lymph ducts and the lymph nodes (as part of the lymphatic system) used to fight any infection.

The proportions of adipose and fibroglandular tissues in the breast vary with age, the general state of nutrition, and with hormonal changes due to menstruation or pregnancy [63], [64]. Breasts with higher proportion of fibrous or glandular tissues compared to fatty tissues are classified as dense breasts. Younger woman tend to have higher breast density, which decrease with the age for most woman but changes little for others [64].
Breast Imaging Reporting and Data System (BI-RADS) defines four levels of breast density. BI-RADS was established by the American College of Radiology (ACR) and is used by radiologists to categorise their findings from the analysis of a mammogram, an Ultrasound image or an MRI into a well-defined category. Table 2.1 describes the four classes of breasts [65].

<table>
<thead>
<tr>
<th>Breast Classes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class I</td>
<td>The breasts are almost entirely fatty.</td>
</tr>
<tr>
<td>Class II</td>
<td>The breasts contain scattered fibroglandular tissues.</td>
</tr>
<tr>
<td>Class III</td>
<td>The breasts are heterogeneously dense.</td>
</tr>
<tr>
<td>Class IV</td>
<td>The breasts are extremely dense.</td>
</tr>
</tbody>
</table>

2.2 Breast Cancer

Breast cancer is defined as abnormal growth of breast cells. Cancer is caused by mutations or abnormal changes in the genes. Genes within the nucleus of the cell control the process of cell division, which regulates cell growth. Over time, mutations in some genes result in uncontrolled division of cells, producing more copies of itself than a normal cell. This abnormal growth results in a tumour [64]. Some tumours remain within the normal boundaries of the tissues and are classified as benign tumours. However, malignant tumours break through normal tissue boundaries and spread to neighbouring tissues. Benign tumours have slower growth rates and are not considered life-threatening; whereas malignant tumours are cancerous and can spread to other parts of the body.

Breast cancer typically begins in lobules or ducts that carry milk from lobules to the nipple. Breast carcinoma is a type of cancer that begins in the epithelial cells and is the most prevalent breast cancer type [64]. The types of breast cancer that start in other breast tissues include sacromas and lymphomas. Sacromas typically start in the cells of muscle, fat and connective tissues [64]. However, the sacromas
and the lymphomas are less common, with breast carcinomas (also referred to as adenocarcinomas) constituting more than 95% of all breast cancers [66].

Breast cancer is broadly classified as non-invasive cancer (carcinoma in-situ) or invasive cancer (invasive carcinoma). Carcinoma in-situ (CIS) stays within the lobules or the ducts where it originally developed, whereas invasive carcinoma cells break through the lobular and ductal wall and spread into the surrounding fibrous and connective tissues. Both invasive carcinoma and CIS can be further classified into ductal or lobular carcinomas based on the site from which the tumour originated [66]. The following are the most common types of breast cancer:

- **Ductal Carcinoma In-situ (DCIS)**
- **Lobular Carcinoma In-situ (LCIS)**
- **Invasive Ductal Carcinoma (IDC)**
- **Invasive Lobular Carcinoma (ILC)**

Both DCIS and LCIS are early-stage cancers, with DCIS being the most common type of non-invasive cancer, accounting for almost 20% of all newly diagnosed cancers [67]. However, LCIS is less common and accounts for only 1-2% of all breast cancers [67]. While CIS is generally not life-threatening, women diagnosed with CIS are considered to be at high risk of developing invasive cancer. However, a recent study has shown that CIS is not a definite precursor of invasive breast cancer [68], [69].

IDC is the most common invasive breast cancer accounting for 55% of all breast cancers [66] and ILC is second to the IDC in terms of incidence rate accounting for 5-15% of all breast cancers [66]. Other less common types of breast cancers include “inflammatory breast cancer” and “Paget’s disease”. Both of these cancers are very rare and account for only 1% of breast cancers [70].

Despite these various types of breast cancers, all cancerous tissues have distinctive features and properties compared to normal breast tissues. These distinguishing features and properties are exploited by the various imaging technologies to detect
and diagnose breast cancer. The following section describes the dielectric properties of normal and cancerous breast tissues that can be exploited by the microwave breast imaging systems for the detection of breast cancer.

2.3 Dielectric Properties of Breast Tissues

Dielectric properties describe the interaction of electromagnetic waves with biological tissues at a cellular and molecular level. When an electric field is applied to biological tissues, the electric field will cause the randomly oriented molecules to align according to the direction of the applied electric field. This alignment under the influence of the external electric field results in polarisation of the molecules within the tissues. This polarisation of molecules induces an electric field in an opposite direction to the applied field, which is smaller in magnitude \[71\]. This process of polarisation is not instantaneous and occurs over a time known as the relaxation time \(\tau\). The resistance offered by the molecules to the applied external electric field can be described by the complex permittivity of a material given as \[72\], \[73\]:

\[
\varepsilon = \varepsilon_0 (\varepsilon'_r - j\varepsilon''_r) \tag{2.1}
\]

where \(\varepsilon'_r\) is the relative permittivity or dielectric constant, \(\varepsilon''_r\) is the loss factor and \(\varepsilon_0\) is the permittivity of a vacuum expressed in Farads per metre (F/m). The loss factor can be expressed as :

\[
\varepsilon''_r = \frac{\sigma}{\omega} \tag{2.2}
\]

where \(\sigma\) is the conductivity of the material expressed in Siemens per metre (S/m) and \(\omega\) is the angular frequency expressed in radians per second.

The frequency dependence of the permittivity (as noted in Equations 2.1 and 2.2) or the dielectric dispersion of the biological tissues can be described by the relaxation time associated with the frequency.

Early studies on the dielectric properties of the human tissues at microwave frequencies were reported by England and Sharples \[74\], \[75\] in 1949-1950, and by Cook in 1951 \[76\]. These studies were performed to investigate the therapeutic use
of microwaves. Since then several studies have been performed to measure a wide variety of normal and malignant human tissues (including breast tissue) \[25\], \[44\], \[77\]–\[80\] and extensive reviews of these studies have been published \[72\], \[81\]–\[83\].

A significant contrast in the dielectric properties between normal and malignant breast tissues was reported by all historic studies. However, there were also variabilities and some inconsistencies between different studies in terms of reported permittivity and conductivity values \[82\]. In particular, the reported contrast between the permittivity of malignant and normal breast tissues varied between 200 and 500\% \[44\]. These inconsistencies were highlighted and analysed by Ward et al in their review of the dielectric properties of normal and malignant breast tissues published in 2002 \[82\].

Ward et al noted that there were ambiguities in the categories of breast tissues reported in the literature. Ward et al attributed the inconsistencies to the differences in the experimental methods and the intrinsic heterogeneity of the breast. The differences in the experimental methods include the tissue sample storage, \textit{in-vivo} versus \textit{in-vitro} measurements, and the temperature of the environment during the measurement. The composition of normal breast tissue (including breast fat, connective tissue and the gland tissue) may also have varied between different samples.

Different stages of the tumour in different malignant samples may have introduced variation in the dielectric properties of tumour tissue. The malignant tissue containing largely normal cells and only few malignant cells may also result in different dielectric properties than the malignant tissue containing all malignant cells. The variation between tissue samples of different patients in terms of tissue water content and fat content, different stage of menstruation, pregnancy or lactation may also have effected the measurements. However, with so many uncontrollable conditions, all studies consistently reported lower mean permittivity and conductivity for fat tissues, while malignant tissues were reported to have higher permittivity and conductivity values than normal breast tissues.
In order to address the above discussed discrepancies, in 2007, Lazebnik *et. al* performed a large scale study of the dielectric properties of normal breast tissue across a wide frequency range of 0.5 to 20 GHz [84]. Some distinctive features of this study include:

- Careful design of the experimental procedures;
- Large number of measurements (i.e. 488 from 93 patients);
- Wideband measurements (0.5-20 GHz);
- Histopathological analysis of the tissue samples and correlation of histopathological analysis with the measured dielectric properties;
- Use of breast tissue samples from breast reduction surgeries instead of cancer surgeries in order to ensure the exclusive measurement of the dielectric properties of healthy breast tissues;
- Use of a broadband small-diameter precision open-ended coaxial probe, with a small sensing volume to precisely measure the dielectric properties of the tissue just beneath the probe;
- Statistical analysis of results and fitting of data using a Cole-Cole model.

Lazebnik *et. al* characterised breast tissues in three groups based on the percentage of adipose tissue contained in the sample. The categorisation of the tissues is described in Figure 2.2.

![Figure 2.2: Normal breast tissue characterisation based on percent adipose content](image)

The measured values of the dielectric properties of breast tissues spanned a wide range between the high adipose content (low-water-content) group to the low...
adipose content (high-water-content) group. The consistent trend of a decrease in the
dielectric properties paired with an increase in the adipose content was observed. The
lowest dielectric properties were observed for the high adipose content tissues (Group
3) and the highest dielectric properties were observed for the low adipose content
tissues (Group 1). There was variability in the dielectric properties within each
group. Group 3 exhibited the lowest variability due to the dominant adipose content
and the homogeneity of the tissue. Both Group 1 and 2 contained heterogeneous
mixture of fibroconnective, glandular and some adipose tissue. Therefore, Group 1
and 2 had a larger variability compared to Group 3. Group 2 exhibited the highest
variability among the three groups. The larger variability in Group 2 is attributed
to the heterogeneity in the composition of this group.

Overall this large scale study established that the composition of normal breast
tissue and the corresponding dielectric properties are much more heterogeneous
across the microwave range than previously reported in most of the studies, with
the exception of Campbell et. al [25]. Lazebnik et. al attributed these differences
to the tissue specimens used in previous studies, which were possibly taken from
a site distinct (far away) from the tumour. Such a tissue sample was likely to
contain a higher adipose content and lower dielectric properties. Moreover, a
decrease in the dielectric properties of Group 3 (85-100% adipose content) tissue
with an increase in the time between the excision and measurement was observed.
However, the magnitude of change was smaller compared to a much larger variation
of dielectric properties within all tissue groups.

In a subsequent study, Lazebnik et. al reported the dielectric properties of normal,
benign and malignant breast tissue obtained from cancer surgeries (lumpectomies
and mastectomies) and excisional biopsies [42]. The experimental procedures
were largely identical to the previous study [84]. An even larger sample size was
used in this study (319 measurements from 196 patients). However, only 160
samples were used in the study after applying exclusionary criteria to minimise
any measurement or histological uncertainty.
The dielectric properties of normal breast tissues obtained from cancer surgeries were compared with those reported in the previous study [84]. There were differences in the properties of all three tissues groups between the two studies. However, the differences in properties from Group 1 and Group 3 between the two studies were relatively small and were within the variability exhibited within individual groups. The differences in the properties of Group 2 were larger between the two studies. These differences were primarily attributed to the characterisation of normal tissue samples between the two studies. Normal tissue samples from breast cancer surgeries had higher adipose content than normal tissue samples from breast reduction surgeries. The higher adipose content in normal tissue samples from cancer surgeries was due to the selection of measurement sites. The measurement site for normal tissues were chosen to be away from the tumour site. Since most tumours in this cancer surgery study originated in glandular tissues, the composition of normal tissues had less glandular content and higher adipose content.

Next, the dielectric properties of malignant tissue were compared to the dielectric properties of normal tissue. A comparison was performed between the dielectric properties of cancerous tissue samples (primarily composed of the malignant glandular and fibroconnective tissues) and normal tissue samples with a maximum of 10% adipose content. The restriction on the adipose content ensured that measurements were exclusively from malignant tissue and there was no high adipose content to bias the measurements. A contrast was observed between the dielectric properties of normal and cancerous tissues but this contrast was much lower than what was reported in previous studies. There was an 8% contrast in the dielectric constant and a 10% contrast in the effective conductivity of normal and cancerous tissues. However, direct comparison of normal glandular and malignant glandular tissues did not show a statistically significant difference in comparison with the dielectric properties of normal glandular and malignant glandular tissues.

In summary, the dielectric properties of malignant tissue observed by Lazebnik et al were consistent with the previous studies [25, 44, 77, 78]. However, the contrast between normal and malignant tissue was no more than 10% as opposed
to the 300-500% contrast reported by Chaudhary et. al [44] and 200-500% contrast reported by Joines et. al [78]. The higher contrast in the previous studies was attributed to the high adipose content normal tissue used in those studies. In both studies, the effects of sample temperature (within the observed range), time between measurement and excision, and patient age, were found to be negligible.

These two studies by Lazebnik et. al [42], [84] are the most comprehensive ex-vivo studies on the dielectric properties of breast tissues to the date. In these studies, Lazebnik et. al also claimed that the in-vivo measurements would not change the dielectric properties measured ex-vivo. However, in a later study, Halter et. al contended that electrical properties measured ex-vivo are different from the in-vivo measurements [85], [86], as previously shown by Casas et. al [87] and Haemmerich et. al [88]. Halter et. al performed a small-scale study of six women. In this study, the electrical properties of the breast were measured in-vivo using: an Electrical Impedance Spectroscopy (EIS) probe; a Microwave Impedance Spectroscopy (MIS) probe; Electrical Impedance Tomography (EIT); and Microwave Tomography (MT). The same tissue specimen measured in-vivo, were excised and measured ex-vivo using the EIS and MIS probes. However, the probes used in ex-vivo measurements were different from the probes used for in-vivo measurements. The in-vivo measurements required a minimally invasive technique to minimise perturbation introduced by probe invasion; whereas ex-vivo probes were designed to provide more robust measurements.

Halter et. al found similar values of the permittivity and the conductivity from ex-vivo measurements as reported by Campbell et. al [25] and Lazebnik et. al [42]. However, substantial decreases in both the conductivity and the permittivity were observed in the excised tissue measured ex-vivo over the microwave frequency range. Halter et. al attributed the decrease in the dielectric properties of the excised tissue to temperature changes, tissue dehydration and ischemic effects. The small sample size used in this study is not enough to make a definite conclusion. However, it does suggest the need for further investigation of in-vivo dielectric properties of the breast.
One of the key findings in Lazebnik’s study was that the breast tissues are highly heterogeneous. The 60 cancerous tissue samples measured in the study were primarily composed of malignant glandular and the fibroconnective tissues as well as healthy glandular and adipose tissue. More specifically, 50 of the 60 cancer samples contained 0-20% adipose tissue and all 60 contained 10% or less glandular tissue. The tissue composition in terms of percentages of adipose, glandular and fibroconnective tissues were visually evaluated by a pathologist. Some of the cancer samples included for determining the dielectric contrast between normal and malignant tissue had malignant tissue content as low as 30%. Therefore, the average dielectric properties of the inhomogeneous cancerous samples may not be representative of the dielectric properties of cancerous tissues. This was highlighted by Sugitani et. al in a recent study of the dielectric properties of breast tissue where they correlated the measured dielectric properties of the tissue sample to the volume fraction of the cancer cells present in the measured tissue sample.

Sugitani et. al studied 102 normal and malignant breast tissue samples of 35 patients and found similar dielectric properties to those reported by Lazebnik et. al. The dielectric contrast was found to be 4:1 between cancer and adipose tissues but no significant contrast was found between cancer and stroma (fibroglandular) tissues. However, significant variations were noted in the dielectric properties of cancer tissues between different samples (not highlighted in the Lazebnik study).

Sugitani et. al computed the three-dimensional volume fraction of cancer in the malignant tumour by counting the pixels of cancer cells from a photomicrograph of the histology slide of the malignant tumour tissue. This computerised method of computing volume fraction of cancer cells in the malignant tissue sample was a key difference in this study compared to the Lazebnik study. The tumour tissue was found to contain cancer cells as well as stroma or fibroglandular cells, as observed in the Lazebnik study. However, the volume fraction of the cancer cells was computed more accurately using a computerised method in contrast to the visual analysis of the histology slide of the malignant tumour sample by a pathologist in Lazebnik study.
Sugitani et. al found 10-80% glandular tissue content and negligible adipose tissue content in the tumour tissue, in contrast to 0-20% adipose content and only 10% or less glandular tissue content reported by Lazebnik. Further, Sugitani used the Bruggeman’s effective medium approximation theory [89] to compute the effective permittivity and conductivity of tumour tissue based on the volume fraction of cancer and stroma cells present in the measured tissue sample. Both the computed dielectric constant and conductivity were compared with the measured values from the tumour tissue specimen.

Higher permittivity was observed with higher density of cancer cells and lower permittivity was observed with lower density of cancer cells. The main conclusion from this study was that the variability in the dielectric properties of tumour tissue can be attributed to the volume fraction of the cancer cells in the measured tissue sample.

In another related study, Meaney et. al evaluated the sensing volume of the open-ended coaxial dielectric probe in two-layer compositions consisting of a background liquid and a planar piece of Teflon [90]. The authors found that the material within the first few hundred microns exerts the dominant influence on the estimated properties measured by this probe. Therefore, the results from Meaney’s study suggest that the open-ended coaxial probe may not be appropriate to measure the compositional averages of the tissue specimen such as tumour tissue that is a heterogeneous mixture of tissues. Lazebnik et. al used a similar open-ended coaxial probe to measure the dielectric properties of tissue in the studies described previously. Meaney et. al suggested that the dielectric contrast reported by Lazebnik may not be correct because of the described limitation of the open-ended coaxial probe used in her studies.

Both Lazebnik’s studies and later studies (for example [91]) are in agreement on the heterogeneous nature of breast tissues. However, since Lazebnik did not consider important confounders (such as sensing volume and volume fraction of cancer cells per sample) as highlighted in the later studies [90], [91], the contrast between normal and cancerous tissues may have been underestimated in Lazebnik’s
studies. These later studies warrant the need for a more comprehensive study to establish a definitive knowledge of the true dielectric contrast between normal and malignant breast tissue. However, Lazebnik studies are the most comprehensive and experimentally sound studies to date and the dielectric properties reported in these studies remain as the reference standard to develop microwave breast imaging and treatment applications.

2.4 Microwave Imaging

The use of microwaves for imaging organs dates back to as early as 1970s when Jacobi and Larsen successfully imaged canine kidneys [92]. Microwave imaging of the breast or any human organ involves illuminating the organ with an electromagnetic field and measuring the scattered field. The characteristics of the scattered field depend on the dielectric properties of the scattering object. The measured scattered field can be processed in several ways to reconstruct an image of the scattering object.

Microwave tomographic imaging of the breast reconstructs the dielectric profile of the breast using inverse scattering algorithms. Typically, in this method, an antenna array is employed where each antenna element of the array in turn illuminates the breast with a low power microwave signal. The scattered response is then recorded at all other antenna elements in the array.

The inversion of the measured scattered field can produce an estimate of the spatial distribution of the dielectric properties of the breast. However, the relationship between the scattering object (the breast tissues) and the scattered field is non-linear. Therefore, a non-linear inversion is required. Iterative methods such as Distorted Born Iterative Method [93], and Newton-based methods [94] may be used to solve the non-linear inverse problem [93–95].

The iterative inversion methods require a set of simulated electric fields in addition to the measured electric fields collected from the target breast to reconstruct target breast image. The simulated electric fields are collected from a numerical model of the breast with known dielectric properties. In the first iteration, the numerical breast model is assumed to have a homogeneous distribution of known
dielectric properties. In subsequent iterations, an updated estimate of dielectric properties from the previous iteration is used. The simulation at each iteration requires solving the forward scattering problem using a forward solver, such as the Finite-Difference Time Domain (FDTD) method. The forward solver calculates the scattered fields from the numerical breast model by solving the Maxwell’s equations. The iterative algorithm aims to minimise the error between the measured and the simulated electric fields. However, the non-linear optimisation has non-unique solutions, and requires regularisation to overcome ill-posedness. Additionally, the iterative algorithms are computationally intensive.

A clinical prototype demonstrating microwave tomography was proposed as early as 2000 by Meaney et al. The prototype was used in a small scale pilot study that reported the average dielectric properties of breast tissues measured in-vivo. Since then, several reconstruction algorithms have been developed to address the inherent non-linearity, ill-posedness and the reconstruction times of the microwave tomography. More recently, a microwave tomography prototype has been used in monitoring the neoadjuvant chemotherapy treatment of breast cancer. The study successfully correlated the change in dielectric properties of the breast to the treatment response in eight patients.

Radar-based microwave imaging is another approach to image the breast and is named Confocal Microwave Imaging (CMI). Unlike microwave tomography that solves a non-linear inverse problem, CMI exploits the phase of the scattered microwave signals to find the location of the dielectric contrast due to the presence of a scatterer in the imaging domain. While microwave tomography aims to reconstruct the spatial distribution of dielectric properties within the breast, CMI can only provide information on the shape, size and the location of the tumour (if any) present within the breast.

The advantage of CMI is that it avoids several challenges associated with microwave tomography, such as non-linearity, ill-posedness and relatively long image reconstruction times associated with the microwave tomography. Further details on CMI are provided in the next section.
2.5 Confocal Microwave Imaging

In CMI, the breast is illuminated with a UWB pulse originating from number of antennas located at different positions near the breast. The UWB pulse propagates into the breast and is scattered by interaction with different breast tissues. The energy of the scattered signal depends upon the dielectric properties of the breast tissues. The tumour reflects more energy due to higher dielectric properties compared to normal breast tissues. The reflected signals are recorded and then combined together to locate regions of dielectric scatterings within the breast.

Two common data acquisition approaches used in a CMI system are the monostatic and the multistatic configuration. In the monostatic approach, the scattered response is recorded only on the same antenna that illuminates the breast. While in the multistatic approach, the scattered response is recorded at all antenna elements of the array. The multistatic approach offers spatial diversity by allowing the observation of the target (e.g. tumour) from different look-angles. However, the multistatic approach is limited by the number of antennas that can be employed in the antenna array to scan the breast. The monostatic approach has the advantage of a large number of measurements that can be taken by moving a single antenna around the breast. However, a large number of measurements come at the cost of an increased scan time.

Signals acquired using either the monostatic or the multistatic approach are focused for each synthetic focal point within the breast to reconstruct an intensity map of the breast. The highest intensity focal points within the intensity map correspond to the location of the dielectric scatterer (e.g. tumour) that has higher dielectric properties than normal breast tissues.

The seemingly simple CMI approach involves a number of challenges. Some of the challenges in the CMI reconstruction of the breast involve the design of a suitable clinical prototype:

- that has high signal-to-noise ratio (SNR);
- that can efficiently direct and couple microwave energy into the breast;
• that can illuminate the breast and record measurements at large number of points around the breast.

Other challenges involve processing the received signals to form breast images. The focus of this thesis is the development and evaluation of effective signal processing algorithms to produce high quality CMI images. The related challenges are described in detail in the following sections.

2.5.1 Artifact Removal Algorithms

The received radar signals in a CMI system are dominated by the early-time artifact. The early-time artifact is composed of the input signal, reflections from the breast skin and any antenna reverberations. The early-time artifact removal is one of the key signal processing challenges in any CMI system.

In 1999, Fear et al. [104] modelled the skin layer of the breast as the solid cylinder of the same size as the breast model (a finite cylinder with dielectric properties of breast) used in the experiment. An approximation of the skin reflection was computed by separately illuminating the solid cylindrical model of skin. The approximated skin signal was subtracted from the total recorded signal recorded from the breast model, which greatly reduced the skin reflection.

In 2000, Fear et al. [105] presented a comparison of this phantom skin subtraction algorithm [104] and the average subtraction algorithm. The average subtraction method assumed that the artifact (skin reflection and incident pulse) appeared at the same temporal location in the backscattered signals recorded at each channel, and could therefore be estimated as an average of the signals recorded at each channel. The artifact was then removed by subtracting this estimated artifact-signal from each backscattered signal:

\[
s_i[n] = b_i[n] - \frac{1}{N} \sum_{i=1}^{N} b_i[n]
\]

(2.3)

where \( b_i[n] \) is the vector containing the signal recorded at channel \( i \), \( N \) is the total number of channels and \( s_i[n] \) is the artifact-free signal. Both methods successfully reduced the artifacts including skin reflections. However, the skin
phantom subtraction algorithm proved to be quite robust compared to the average subtraction algorithm, which is more effective when antennas are closely spaced. The averaging method was also adopted by Li et al. in [41].

In 2003, Bond et al. [35] developed an adaptive filtering based artifact removal algorithm. This algorithm improved on the simple Average Subtraction method by compensating for channel-to-channel variation in artifacts due to local variation in skin thickness, breast heterogeneity and differences in antenna-skin distances. In this method, the artifact in each channel is estimated as a filtered combination of the signals in all other channels. The estimated artifact signal for channel $i$ is then subtracted from the received signal at channel $i$.

In 2005, Sill et al. [36] developed the Recursive Least Squares (RLS) algorithm for artifact removal. RLS is an adaptive filtering algorithm that recursively computes and updates the filter weights, in contrast to the Wiener Filter [35] method that shifts constant weight vectors through the selected window.

In 2006, Zhi et al. [37] proposed the Entropy-based Time Window (EBTW) artifact removal algorithm. The algorithm is based on the assumption that the artifacts in the received signals are highly similar across all channels. This is not the case for the tumour response, as it is delayed and attenuated differently in each channel. Entropy is a measure of the variation of the signal, where entropy is inversely proportional to the amount of variation. Therefore, a larger value of entropy is obtained from similar artifacts in the early portion of the radar signal and conversely, the tumour reflections result in a much lower entropy value. A window function was defined based on the entropy values of the signals and the artifacts were removed by multiplying the window function with the received signal at each channel.

Klemm et al. [47] proposed the Rotation Subtraction method, which required two separate radar measurements. The first set of measurements was recorded with the circular antenna array surrounding the breast in one position and a second set of signals was recorded after the antenna array had been rotated at a certain angle in the horizontal plane around the vertical axis, as follows:

$$s_i[n] = b_i[n] - b_r[n]$$  \hspace{1cm} (2.4)
where \( b_r[n] \) is the vector containing the signals recorded after the antenna array had been rotated.

In 2009, Maskooki et al. [38] proposed a frequency-domain artifact removal algorithm. The principle of this algorithm is to represent the frequency response of each received radar signal as a sum of complex exponentials, where each complex exponential represents a pole of the system and each pole corresponds to a specific scatterer in the view of the antenna. The artifacts can then be removed by removing the pole corresponding to the strongest scatterers from the frequency response (assuming the skin is the strongest scatterer).

2.5.2 Imaging Algorithms

The imaging algorithm combines the received signals to produce an intensity image of the breast that allows for localisation of the tumour. While the artifact removal algorithm significantly reduces the early-time artifacts, there are still various factors that impact the performance of the imaging algorithm. The electromagnetic waves suffer attenuation as they propagate through the breast. Due to the highly dispersive and lossy nature of breast tissues, the tumour response is highly attenuated in the received signals. An effective imaging algorithm discriminates the tumour response from the clutter by various signal processing techniques. The clutter is mainly caused by reflections from the heterogeneous healthy breast tissues and multipath scattering effects. The varying propagation speed of the electromagnetic waves in heterogeneous tissue is another source of artifacts in the images produced by an imaging algorithm.

The aim of any imaging algorithm is to improve the tumour response while suppressing the clutter. Several imaging algorithms have been reported in the literature and are classified in two categories: DI and the DA. Both DI and DA algorithms are based on the coherent addition of the received radar signals. However, DI algorithms use an assumed propagation model and the frequency-dependent propagation effects are compensated for based on an assumed propagation model [35], [39], [40], [45], [46], [49], [106], [107]. In contrast, the DA algorithms estimate the
propagation model from the received signals and apply compensation factors based on the estimated channel model [108].

The following section provides an overview of the various imaging algorithms developed for CMI of the breast.

2.5.2.1 Data-Independent Beamforming Algorithms

In 1998, Hagness et al. [43] developed a two-dimensional (2D) monostatic Delay-And-Sum (DAS) beamformer for the detection of breast cancer. In the DAS beamformer, the overall breast is divided into a large number of synthetic focal points. The backscattered radar signals are synthetically focused at each focal point. This focusing involves time-alignment, summation and then integration of the received signals for each synthetic focal point $\vec{r} = (x, y)$ within the breast. The backscattered energy profile of the breast is reconstructed as follows:

$$ I(\vec{r}) = (\sum_{i=1}^{M} B_i(\tau_i(\vec{r})))^2 \quad (2.5) $$

where $B_i$ is the backscattered signal recorded at channel $i$, $\tau_i$ is the time-delay corresponding to focal point $r$ and $M$ is the total number of channels.

The reflections from the breast add coherently for the focal point corresponding to the tumour location and the reflections from focal points corresponding to normal breast tissues add incoherently. The highest energy in the reconstructed energy profile is assumed to represent the location of the tumour.

Li et al. [41] extended the DAS [43] beamformer and introduced a weighting factor in order to compensate for the radial spreading of the illuminating signal as it propagates into breast tissues. Each backscattered radar signal was multiplied by a weighting factor $w_i$ before the coherent addition process. Equation 2.5 was modified to reconstruct the energy profile of the breast as follows:

$$ I(\vec{r}) = \left( \sum_{i=1}^{M} w_i \cdot B_i(\tau_i(\vec{r})) \right)^2 \quad (2.6) $$

Several methods [49], [106], [107] were proposed to compute the weighting factor $w_i$ in Equation 2.6. Fear et al. [40] used $1/r_0$ as a weighting factor where $r_0$ is the
distance between the transmitting antenna and the focal point to compensate for the radial spreading. In addition, a compensation factor for the path loss/attenuation was also explored. However, it was found that path loss compensation enhanced the early-time clutter in signals.

Fear et al. [40] investigated the feasibility of planar and circular antenna configurations for CMI systems. In addition, the study combined several important preprocessing steps in the CMI reconstruction. One of the most important steps introduced in this study was the use of the Average Subtraction algorithm for the early-time artifact removal. The other preprocessing steps included the integration of received time signals and the compensation for the radial spreading and the path loss. The integration step was similar to the one previously used by Li et al. [41]. After integration, the tumour response occurs at a local maximum allowing for coherent addition after time-alignment. These preprocessing steps were combined with the DAS algorithm to produce images with both planar and cylindrical configurations. The study indicated that both planar and cylindrical configurations successfully detected and localised the tumour with similar image quality in simplistic three-dimensional breast models.

Nilavalan et al. [109] proposed the first multistatic DAS beamformer in order to reconstruct a breast image from radar signals acquired using the multistatic radar approach. The multistatic focusing was first introduced by Benjamin for the detection of buried mines in the field of GPR [110]. The basic principle is the same as the standard DAS described by Hagness et al. [43]. However, Hagness only used monostatic backscattered radar signals in the image reconstruction. It is assumed that an increased number of received radar signals in the multistatic approach would carry more information about a strong scatterer, such as a tumour present within the breast. Therefore, the proposed method allowed for improved tumour detection and localisation capabilities compared to the monostatic DAS [41]. Nilvalan reconstructed the energy profile of the breast as follows:

\[
I(\vec{r}) = \int_0^T \left( \sum_{i=1}^{M(M-1)/2} w_i \cdot B_i(\tau_i(\vec{r})) \right)^2 \, dt \quad (2.7)
\]
where $T$ is the length of time-window corresponding to width of the incident pulse.

Lim *et al.* [111] proposed another method to virtually increase the number of radar signals for the image reconstruction. Lim *et al.* proposed the Delay-Multiply-And-Sum (DMAS) beamformer, which is similar to the multistatic DAS [109] with an additional multiplication step. However, DMAS offers better clutter reduction capability compared to DAS which is achieved by pairing multiplication and virtually increased sample size. In the DMAS algorithm, the artifact-free signals are time aligned, multiplied in pairs and then summed for each focal point $r$ of the breast. The summed signal is then integrated over a time-window to compute the energy corresponding to each focal point. The integration window is defined by the pulse width of the transmitted signal. Better clutter rejection capability of the DMAS was demonstrated by the successful detection of very small (2 mm diameter) tumours. It was also observed that a shorter integration window improved the detection and localisation of tumours. The algorithm was applied to both monostatic and multistatic radar signals and it was shown that the multistatic approach outperformed the monostatic approach. However, the algorithm was only evaluated using relatively simplistic breast models.

Klemm *et al.* [106] introduced a new method to calculate the weighting factor in the multistatic DAS beamformer [109] to improve the image quality of reconstructed breast images. In the Improved Delay-And-Sum (IDAS) algorithm, an additional weighting factor named ‘Quality Factor (QF)’ rewards the coherent addition of radar signals based on the quality of the coherence. The QF for each focal point $r$ is calculated from the energy collection curve obtained during the coherent summation of radar signals. The energy collection curve is normalised using multiplication by $1/(1 + \sigma_e)$, where $\sigma_e$ is the standard deviation of energy of all signals. The scaling with $\sigma_e$ gives more weight to an energy curve that resembles the ideal energy collection curve. A second-order polynomial ($y = ax^2 + bx + c$) is fitted to the normalised energy collection curve using a least-square fitting algorithm and the coefficients of the second-order polynomial are established. The coefficient $a$ is
chosen as the QF and multiplied with the final energy computed for each focal point. The QF is introduced in Equation 2.7 and is given below:

\[
I(\vec{r}) = QF(\vec{r}) \cdot \left( \sum_{i=1}^{M(M-1)/2} w_i(\vec{r}) \cdot B_i(\tau_i(\vec{r})) \right)^2
\] (2.8)

The IDAS provided significant improvement in image quality compared to the DAS algorithm and it was observed that quality of reconstructed images was comparable to the Robust Capon Beamformer (RCB), which is a much more computational complex DA beamformer as compared to the IDAS.

In a separate study, Klemm et. al [107] presented another method to compute the weighting factor in order to improve the multistatic DAS algorithm. In the new algorithm, the traditional DAS [41] algorithm was modified to include an additional coherence based weighting factor. The Coherence Factor (CF) was adapted from Ultrasound Imaging [112] and it was used to measure and enhance the coherence quality of radar signals. The CF was calculated for each focal point \( r \) as:

\[
CF(\vec{r}) = \frac{\sum_{i=1}^{M(M-1)/2} B_i(\tau_i(\vec{r}))^2}{\sum_{i=1}^{M(M-1)/2} |B_i(\tau_i(\vec{r}))|^2}
\] (2.9)

Then, the final energy was calculated as:

\[
I(\vec{r}) = \int_0^T \left( \sum_{i=1}^{M(M-1)/2} \frac{CF(\vec{r}) \cdot w_i(\vec{r}) \cdot B_i(\tau_i(\vec{r}))}{2} \right)^2
\] (2.10)

The Coherence Factor based DAS (CF-DAS) algorithm was evaluated using inhomogeneous breast phantoms with the dielectric properties based on studies by Lazebnik et al. [42], [84]. Breast phantoms were imaged with and without the CF. In all of the breast phantoms imaged, the addition of CF provided significant improvement in image quality. However, the results were not compared to the IDAS beamformer.

O’Halloran et al. [49] introduced yet another method to compute the weighting factor. In the new Channel Ranked DAS (CR-DAS) beamformer, the round trip distance from each antenna to a synthetic focal point is calculated. Channels with shorter propagation paths that have a relatively clear view of the focal point are less likely to encounter heterogeneity and are less affected by the attenuation and phase
effects. Conversely, the channels with relatively long propagation paths encounter significant heterogeneity and suffer more attenuation as the UWB signals propagates to and from the focal point. Therefore, channels with shorter propagation path can be given extra weighting in the imaging reconstruction process. The weighting factor was calculated as follows:

\[ w(i) = \frac{N - \text{rank}(i)}{N(N + 1)/2} \tag{2.11} \]

where \( N \) is the number of multistatic signals, \( \text{rank}(i) \) is a number from 1 to \( N \), assigned to each signal based on its round-trip propagation distance (signal with the shortest propagation distance is assigned a rank of 1). The weighting factor is applied to each signal prior to coherent summation and formation of energy image.

Distinctive to all above methods, Bond et al. [35] developed the Microwave Imaging via Space-Time (MIST) beamformer in order to compensate for frequency-dependent propagation effects. In the MIST beamformer, the backscattered signals are first time-aligned for specific focal point \( \vec{r}_i \) and then passed through a bank of FIR filters. The filtered signals are summed and the energy is calculated after time-gating the summed signal. The weights of the FIR filters are computed using least squares so that the backscattered signal originating from focal point \( \vec{r}_i \) pass with unity gain while compensating for frequency-dependent propagation effects. The propagation effects such as attenuation and the phase constant are computed from an assumed propagation model of the channel. The process is repeated for each synthetic focal point within the breast and an energy profile of the breast is created. The algorithm was applied to monostatic signals obtained from 2D breast models and a tumour as small as 2 mm diameter was successfully detected in various breast models. A frequency-domain design of MIST beamformer was developed by Davis et al. [113].

O’Halloran et al. [114] extended the monostatic MIST beamformer [35] in order to process multistatic MIST data, resulting in a quasi-multistatic MIST beamformer. The multi-MIST was evaluated on 2D anatomically accurate breast models and it offered improved performance compared to the monostatic MIST.
Davis et al. developed a Generalised Likelihood Ratio Test (GLRT) algorithm that detects tumour location by a statistical method of hypothesis testing [115]. In the GLRT, backscattered signals received by illuminating the breast model are compared with the analytically obtained tumour templates for each synthetic focal point within the breast. The comparison is performed using test statistics and the image is constructed by performing the test statistic for all synthetic focal points (voxels) within the breast. The algorithm is based on the assumption that the tumour size, shape and density is perfectly known. In addition, the dielectric properties of the medium around the tumour and the propagation speed within the surrounding medium must be accurately known. Furthermore, the clutter due to multiple scattering paths within the heterogeneous breast can be modelled as Gaussian. The Gaussian assumption is based on the fact that the sum of scattering returns is Gaussian distributed in the limit according to the Central Limit Theorem [116]. The algorithm was shown to successfully detect small tumours in numerical as well as experimental breast phantoms in low dielectric contrast scenarios. However, the algorithm failed to correctly detect tumours in heterogeneously dense cases.

2.5.2.2 Data-Adaptive Beamforming Algorithms

In general, DA beamforming algorithms provide better resolution and superior interference/clutter rejection capabilities in comparison with standard DI counterparts. DA methods adaptively assign weights to the signals based on their direction-of-arrival. Higher weights are assigned to the signal-of-interest, whereas the interference from unwanted scatterers is suppressed, resulting in higher performance than DI beamforming approaches.

Several DA beamforming algorithms have been proposed in the literature. In 2003, Li et al. [117], [118] extended the Capon beamformer in order to improve robustness. The Standard Capon Beamformer (SCB) estimates the signal energy by adaptively selecting a weight vector for the received signals. The weight vector is chosen to minimise the beamformer output power subject to the constraint that the signal of interest (SOI) does not suffer any distortion. However, in practice, SCB
suffers performance degradation from imprecise knowledge of the array steering vector, which is often caused by waveform distortions, antenna location uncertainties and time-delay roundoffs. The presence of coherent interferences also contributes to the performance degradation of SCB. To mitigate the performance degradation due to steering vector errors, Li et al. introduced an ellipsoidal uncertainty set of steering vectors in the SCB making the beamformer less sensitive to steering vector mismatches.

Consider the following preprocessed signal vector for a focal point $r_0$:

$$y(t) = [b_1(t) \ b_2(t) \cdots b_M(t)]^T, \ t = 0, \cdots, N - 1 \quad (2.12)$$

Each snapshot $y(t)$ can be modelled as:

$$y(t) = a(t) \cdot s(t) + e(t) \quad (2.13)$$

where $s(t)$ is the backscattered signal, $a$ denotes the steering vector, and $e(t) = [e_1(t) \ e_2(t) \cdots y_M(t)]$ includes the noise and interference due to undesired reflections.

Assuming proper time alignment and signal compensation, the steering vector can be assumed to be $a = [1, \cdots, 1]^T$. With the knowledge of the steering vector, $s(t)$ can be estimated from $y(t)$.

RCB assumes that the true steering vector $\hat{a}(t)$ lies in the vicinity of the assumed steering vector, $a$ and the only knowledge available about $\hat{a}(t)$ is that $\|\hat{a}(t) - a(t)\|^2 \leq \epsilon$, where $\epsilon$ is a user defined parameter to describe the uncertainty of $\hat{a}(t)$ [51], [53]. The steering vector $\hat{a}(t)$ can be determined using a covariance fitting approach described in [51].

Given $\hat{a}(t)$, the RCB problem can be formulated as:

$$\min_w w^T \hat{R} w \quad \text{subject to} \quad w^T \hat{a} = 1 \quad (2.14)$$

where $\hat{R}$ is the sample covariance matrix given as:

$$\hat{R} = \frac{1}{M} y(t)y^T(t) \quad (2.15)$$
and the solution to (2.14) is given as:

$$\hat{w} = \frac{\hat{R}^{-1} \hat{a}}{\hat{a}^T \hat{R}^{-1}}$$

(2.16)

The beamformer output can be written as a vector:

$$\hat{s}(t) = [\hat{w}^T(t)y(t)]^T$$

(2.17)

Finally, the backscattered energy from location \(r_0\) can be calculated as:

$$I(r_0) = \sum_{t=1}^{N} \hat{s}^2(t)$$

(2.18)

**RCB** provided better interference rejection capability than a **DI** beamformer and proved to be computationally efficient.

The **SCB** algorithm was further extended by Guo *et. al* [53] by introducing a weighted sample covariance matrix in the **SCB** formulation. The **Weighted Capon Beamformer (WCB)** assigned more weight to the signal based on the signal content while estimating the covariance matrix. With the new weighting strategy, the **WCB** “focused” on the snapshots (collected time data), where the estimated signal content was large. **WCB** demonstrated the high resolution and clutter suppression properties of the **SCB** but it also suffered from sensitivity to steering vector inaccuracies. Therefore, the **RCB** was adopted to make **WCB** robust against errors in the steering vector, resulting in the **Robust Weighted Capon Beamformer (RWCB)**. The authors also presented the **Amplitude and Phase Estimation (APES)** beamformer, which explicitly assumes that the signal waveform is known. The **APES** beamformer not only inherently suppresses the interference from other scatterers but also protects the signal-of-interest by enforcing quality constraints. Both algorithms were applied to three-dimensional numerical breast models and were compared to two **DI** beamformers, namely **DAS** [41] and **MIST** [35]. It was observed that both **RWCB** and **APES** were robust to interference, when compared to the **DAS** and the **MIST** beamformers.

Xie *et al.* developed a **Multistatic Adaptive Microwave Imaging (MAMI)** beamformer [51] based on the **RCB** [118] algorithm. In **MAMI** the **RCB** algorithm
is applied in two stages. In the first stage, RCB is used spatially to obtain the vector of multiple backscattered signals corresponding to each probing signal. The second stage involves the application of RCB to recover a scalar signal, based on the estimated vectors of signals obtained in first stage. The scalar signal is used to compute the backscattered energy for the focal point $\vec{r}$. The MAMI algorithm was evaluated using three-dimensional numerical breast phantoms and it exhibited higher resolution, lower sidelobes, and better interference rejection capability than the RCB, APES, MIST and DAS.

2.6 Comparative Analysis of Imaging Algorithms

Several studies [48], [51], [54]–[59], [119] have been completed to compare the performance of different beamformers developed for microwave breast cancer detection. This section provides a brief review of those studies.

Xie et. al compared the performance of the MAMI algorithm [51] with the:

- monostatic DAS [41];
- multistatic DAS [109];
- RCB [53];
- APES [53];
- and the MIST [35].

The MAMI outperformed all other algorithms in terms of the image quality. The image quality metrics used in the study were signal-to-clutter ratio and the full-width at half-maximum of the dominant response in the image [40]. The mutistatic DAS and the APES had a comparable performance. Comparatively, the MIST and the monostatic DAS performed worst. The worst performance of the MIST and the monostatic DAS may be attributed to substantially fewer signals (72) used in the image reconstruction compared to a large number of signals (2,556) used by the MAMI and the multistatic DAS.
The study was comprehensive in terms of the number of breast models; different tumour sizes and the number of imaging algorithms examined. However, the breast models used in the study were created from a hemisphere. The hemispherical breast is expected to provide good artifact removal in each channel due to the similarity of the skin reflections at all antenna locations that can be easily reduced even with the simple Average subtraction algorithm used in the study. Furthermore, the hemispherical breast models used in this study were modelled with the dielectric properties and heterogeneity of breast tissues based on historic studies \[44, 77, 120\]. However, the recently reported low dielectric contrast between the tumour and healthy breast tissues and the heterogeneity of healthy breast tissues \[42\] presents a far more challenging imaging scenario for the imaging algorithms than the high dielectric contrast reported in the historic studies \[44, 77, 120\].

In 2009, Klemm et al. \[48\] presented a hemispherical antenna array based experimental breast imaging system, along with a performance comparison of the DAS and modified MAMI beamformers in the presence of preprocessing errors (based on numerical simulations). The comparison was also performed on experimental data. It was concluded that MAMI has better clutter suppression capabilities than DAS but in the presence of preprocessing errors above a certain level, the DAS algorithm performs better than MAMI. However, both numerical simulations and experimental results showed that, with good preprocessing of measured signals, the MAMI provides better image quality compared to simple DAS. Even though the study provided a comparison in both numerical and experimental scenarios, only two imaging algorithms were compared and realistic dielectric properties as well as realistic heterogeneity as reported by Lazebnik et al. \[42\] were not considered.

O’Halloran et al. \[58\] evaluated the effects of fibroglandular tissue distribution on the performance of three DI beamforming algorithms. The study compared the DAS, DMAS and IDAS in terms of various image quality metrics. The study found that both IDAS and DMAS significantly outperform DAS in relatively homogeneous breast models. However, the performance of IDAS and DMAS degrades in more dense breast models where fibroglandular tissue density is higher. In addition to
the performance degradation, it was also noted that the location of the tumour was difficult to establish in the dense breast models due to the strong response of fibroglandular tissues. The study was the first to compare beamforming algorithms by incorporating realistic dielectric properties of the breast tissue, as reported by Lazebnik et. al \cite{42}. The study also used breast models derived from an Magnetic Resonance (MR) image of a realistic breast. However, only 2D slices of breast models were used in the study and an “idealised” artifact removal algorithm was used to reduce the skin reflections, which would be ineffective in practice.

Byrne et. al \cite{119} extended the above study by evaluating DAS, DMAS and IDAS on 3D anatomically accurate breast models. The breast models were derived from MR images of the breast available from the numerical breast phantoms repository of the University of Wisconsin \cite{121}. These numerical breast phantoms are now the most commonly used breast phantoms for the evaluation of microwave breast imaging algorithms. The study incorporated realistic dielectric properties breast tissue, as used in the previous study by O’Halloran et. al \cite{58} and originally reported by Lazebnik et. al \cite{42}. Tumour models with different sizes were generated from Gaussian random spheres, to simulate the realistic shape, surface and textures of tumours.

The study concluded that the DMAS and IDAS outperform the DAS in relatively homogeneous breast models. However, with increasing density of fibroglandular tissues, degradation in the performance was observed for all algorithms. The dominant response in the final images of the heterogeneous model often corresponded to the location of fibroglandular tissue instead of the tumour for all the algorithms. However, in terms of image quality metrics, the monostatic DAS was found to be more robust in the heterogeneous breast models compared to all other algorithms. While the study used different tumour sizes, only one breast model with realistic heterogeneity was used. DA algorithms were not included in the study and only three DI algorithms were selected for the comparison. In addition, an “idealised” artifact removal algorithm was used to reduce the skin reflections.

Kirshin et. al \cite{56} performed a comparative study of both DI and DA beamforming algorithms. The study included the evaluation of DAS, DMAS, and MIST.
GLRT and RCB. The breast model used in this study was composed of a circular region of breast tissues extracted from an MR image and enclosed by 1.6 mm thick skin. The results were quantified in terms of Signal-to-interference-and-noise ratio (SINR), the localisation error, and the Peak-to-sidelobe ratio (PSLR). The 2D breast models were created with varying dielectric contrast between tumour and the healthy tissues. In addition to different tumour locations, the breast models also differed in the level of heterogeneity.

The results indicated that the GLRT exclusively provided reliable tumour detection in low contrast conditions. While the DAS and the DMAS algorithms perform well in medium to high contrast, they fail when the level of heterogeneity is higher. This result is in agreement with the conclusion from the previous two comparative studies. MIST performed only marginally better than DAS and DMAS. RCB performance gradually decreased with the increase in heterogeneity and decrease in the contrast. While RCB and DMAS outperform all other algorithms in terms of clutter suppression, DAS/DMAS outperform all other algorithms in terms of localisation accuracy.

From these mixed results it is difficult to conclude in favour of one algorithm. However, Kirshin’s study chose the GLRT for future investigation due to its superior performance in terms of tumour detection. The study by Kirshin et. al is also comprehensive in terms of the number of algorithms as well the challenging scenarios of varying contrast and heterogeneity. The study used a single 2D circular breast model. In addition, average subtraction based artifact removal algorithm may perform well in the case of a 2D circular breast due to similar skin reflections. However, the performance of an average subtraction algorithm in a realistic 3D anatomically accurate breast model may impact the performance of the imaging algorithms.

In a recent study, Moll et. al compared the performance of four DI beamforming algorithms. The study included the evaluation of DAS, CF-DAS, CR-DAS and the Time-Difference-of-Arrival (TDOA) imaging algorithm. A numerical breast model was developed with spherical regions. The spherical regions
were assigned different dielectric properties to model a heterogeneous breast. A tumour was modelled as a point scatterer. The backscattered data was collected in a bi-static radar configuration. The performance of each algorithm was evaluated and compared using a qualitative evaluation of point spread functions. The study found that all beamformers correctly localise the tumour in a homogeneous breast. However, the performance of all algorithms degrades in a heterogeneous breast. The study only used one breast model and did not consider realistic dielectric heterogeneity. A realistic method to reduce the early-stage artifact was also not used.

More recently Li et al. [59] evaluated the performance of various imaging algorithms using data obtained from a clinical trial of volunteers. The study compared the performance of the DMAS, MIST, WCB and the GLRT algorithms. The clinical trial included scans of 12 healthy volunteers using a time-domain multistatic radar system [123]. The volunteers were scanned multiple times over a period of eight months. The first set of measurements (tumour-free) for each volunteer were used as a baseline. The baseline measurements of each volunteer were subtracted from the subsequent measurements to generate the tumour-free differential signals. Since the volunteers had healthy breasts, modelled tumour responses were injected in the scan data to generate the tumour-bearing signals. The baseline measurements were subtracted from the tumour-bearing signals to generate the tumour-bearing differential signals. The tumour-free and the tumour-bearing differential signals were processed through each imaging algorithm to produce the final images. The maximum intensity in the images was analysed to assess the performance of each algorithm.

The study found that the tumour-bearing DMAS image had higher intensity compared to the tumour-free image. However, significant clutter regions were observed in the DMAS image. The MIST images of tumour-free and tumour-bearing measurements were difficult to distinguish due to significant artifacts. The WCB tumour-bearing image did not show the tumours in the images. However, the GLRT images of tumour-bearing measurement clearly showed the presence of tumour with a maximum intensity significantly higher than the maximum intensity of
tumour-free measurements. The maximum image intensities of the tumour-free and tumour-bearing measurements were used to train a classifier. The GLRT algorithm provided a detection rate of 55% at a false positive rate of 10%, while the detection rate of all other algorithms was less than 10% at the same false positive rate of 10%.

The improved performance of the GLRT algorithm may be attributed to the hypothesis testing approach of the GLRT algorithm. The GLRT algorithm compares the tumour signal template with the received signals for each candidate tumour location. The GLRT algorithm is expected to perform best when an accurate estimate of the tumour signal template is available. If the tumour signal injected in measurements is the same as the tumour signal template used in the GLRT, a higher detection rate is expected from the GLRT. In addition, the differential signal approach may simplify the imaging problem, by effectively removing the early-time artifact due to skin reflections and the late-time clutter due to multiple scattering effects. While the differential approach may be useful in monitoring applications, it has limited usage for diagnostic application where baseline measurements are not available.

In summary, microwave imaging algorithms have been evaluated previously using anatomically and dielectrically inaccurate numerical phantoms [51], [55], [56], while using an idealised artifact removal algorithm and ignoring the impact of realistic artifact removal [54], [57], [58]. The results from the only clinical study on evaluation of imaging algorithms are based on several assumptions, such as the availability of an accurate tumour signature template and the availability of baseline measurements. Therefore, results may not be generalisable to the diagnostic application where baseline measurements are not available and an accurate estimation of the tumour signature template in the unknown breast density is not possible. Therefore, further investigation of the relative performance of the imaging algorithms in realistic experimental and clinical scenarios is required.
2. Literature Review

2.7 Breast Phantoms

Numerical breast phantoms play a vital role in the evaluation of microwave breast imaging algorithms. A variety of numerical breast phantoms ranging from the simple cylindrical [40] and hemispherical models [51], [124] to more anatomically accurate MRI-based breast models [35], [41] have been reported in the literature. However, there were no standard or commonly used numerical breast phantoms available prior to the development of 3D grid-based numerical breast phantoms repository at the University of Wisconsin Cross-Disciplinary Electromagnetics (UWCEM) laboratory [121]. UWCEM breast models are the most common numerical breast phantoms used for the development and evaluation of microwave breast imaging algorithms prior to the clinical validation. In this section, a brief overview of these numerical breast phantoms is presented.

Zastrow et al. [121] derived numerical breast phantoms from T1-weighted MR images of patients scanned in the prone position. Each phantom is a 3D grid of cubic voxels of dimensions 0.5 mm x 0.5 mm x 0.5 mm. The phantoms have an approximately 1.5 mm layer of skin, a 15 m-thick subcutaneous fat layer at the base of the breast and a 5 mm-thick muscle chest wall.

In addition to the skin and the chest wall, each voxel within the 3D grid of the breast phantom represents either fat or the fibroconnective/glandular tissue. The voxels outside the skin layer represent the immersion medium. The breast phantoms are classified based on their radiographic density, as defined by the American College of Radiology (ACR). The classifications are described in the Table 2.2.

Table 2.2: Classification of numerical breast phantoms in the University of Wisconsin Cross-Disciplinary Electromagnetics (UWCEM) repository

<table>
<thead>
<tr>
<th>ACR Class</th>
<th>Radiographic Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class I</td>
<td>mostly fatty (&lt;25% glandular tissue)</td>
</tr>
<tr>
<td>Class II</td>
<td>scattered fibroglandular (25-50% glandular tissue)</td>
</tr>
<tr>
<td>Class III</td>
<td>heterogeneously dense (51-75% glandular tissue)</td>
</tr>
<tr>
<td>Class IV</td>
<td>very dense (&gt;75% glandular)</td>
</tr>
</tbody>
</table>
Normal tissues within the breast are divided into seven tissue types based on their water content. The tissue categorisation used in these phantoms is the same as that reported by Lazebnik et. al [42]. Each tissue type is assigned a numeric code depending on the water content. The highest water-content and the highest dielectric properties fibroglandular tissues are assigned the Media 1.1. Lowest-water content and the lowest dielectric properties fat tissues are assigned the name Media 3.3. In addition to three different water-content fat tissues and the three different water-content fibroglandular tissues, there is another tissue type named transitional tissue. The transitional tissue has intermediate dielectric properties of a fat and a fibroglandular tissue. The different tissue types and the corresponding media numbers are described in Table 2.3.

These breast phantoms are anatomically accurate as they are derived from MR images of real breasts and also incorporate realistic tissue distribution and heterogeneity. These breast models can be used in electromagnetic simulations to evaluate the performance of various microwave breast imaging algorithms. In order to use these breast models in an electromagnetic simulation software, the immersion medium and each tissue within the breast must be assigned the appropriate dielectric properties.

Dispersive dielectric properties can be incorporated using the Cole-Cole or the Debye model. Zastrow et. al [121] presented both single pole Cole-Cole as well as

<table>
<thead>
<tr>
<th>Tissue Type</th>
<th>Media number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Immersion Medium</td>
<td>-1</td>
</tr>
<tr>
<td>Skin</td>
<td>-2</td>
</tr>
<tr>
<td>Muscle</td>
<td>-4</td>
</tr>
<tr>
<td>Fibroconnective/glandular-1</td>
<td>1.1</td>
</tr>
<tr>
<td>Fibroconnective/glandular-2</td>
<td>1.2</td>
</tr>
<tr>
<td>Fibroconnective/glandular-3</td>
<td>1.3</td>
</tr>
<tr>
<td>Transitional</td>
<td>2</td>
</tr>
<tr>
<td>Fatty-1</td>
<td>3.1</td>
</tr>
<tr>
<td>Fatty-2</td>
<td>3.2</td>
</tr>
<tr>
<td>Fatty-3</td>
<td>3.3</td>
</tr>
</tbody>
</table>
single pole Debye parameters to obtain frequency-dependent dielectric properties for each tissue type in a desired frequency band.

In this thesis, Chapters 3-5 use these MRI-based numerical breast phantoms to evaluate the performance of the developed algorithms. Breast phantoms are simulated using an in-house FDTD software. The Debye model can be more readily incorporated into the FDTD simulations. Therefore, the dielectric properties are incorporated into these breast models using the Debye model. The specific Debye parameters used in the FDTD simulations are described in Table 2.4.

Table 2.4: Single-pole Debye parameters for the different tissue types (valid for 3-10 GHz) (© 2008 IEEE. Reprinted, from [121]).

<table>
<thead>
<tr>
<th>Tissue Type</th>
<th>Media number</th>
<th>$\epsilon_\infty$</th>
<th>$\Delta\epsilon$</th>
<th>$\tau$ (ps)</th>
<th>$\sigma_s$ (S/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tumour</td>
<td>23.20</td>
<td>48.35</td>
<td>13.00</td>
<td>1.306</td>
<td></td>
</tr>
<tr>
<td>Skin</td>
<td>-2</td>
<td>15.93</td>
<td>23.83</td>
<td>13.00</td>
<td>0.831</td>
</tr>
<tr>
<td>Muscle</td>
<td>-4</td>
<td>21.66</td>
<td>33.24</td>
<td>13.00</td>
<td>0.886</td>
</tr>
<tr>
<td>Fibroconnective/glandular-1</td>
<td>1.1</td>
<td>14.20</td>
<td>40.49</td>
<td>13.00</td>
<td>0.824</td>
</tr>
<tr>
<td>Fibroconnective/glandular-2</td>
<td>1.2</td>
<td>13.81</td>
<td>35.55</td>
<td>13.00</td>
<td>0.738</td>
</tr>
<tr>
<td>Fibroconnective/glandular-3</td>
<td>1.3</td>
<td>12.99</td>
<td>24.40</td>
<td>13.00</td>
<td>0.397</td>
</tr>
<tr>
<td>Transitional</td>
<td>2</td>
<td>8.49</td>
<td>13.97</td>
<td>13.00</td>
<td>0.238</td>
</tr>
<tr>
<td>Fatty-1</td>
<td>3.1</td>
<td>3.987</td>
<td>3.545</td>
<td>13.00</td>
<td>0.080</td>
</tr>
<tr>
<td>Fatty-2</td>
<td>3.2</td>
<td>3.116</td>
<td>1.592</td>
<td>13.00</td>
<td>0.050</td>
</tr>
<tr>
<td>Fatty-3</td>
<td>3.3</td>
<td>2.848</td>
<td>1.104</td>
<td>13.00</td>
<td>0.005</td>
</tr>
</tbody>
</table>

2.8 Experimental Prototypes

Several experimental prototypes for CMI of the breast have been developed. Most of these prototypes are still in experimental stages. However, a number of these prototypes have been used in patient studies in clinical environments. In this section, a brief overview of the prototypes that have been used in patient studies is presented.

The University of Bristol has developed several hardware prototypes starting with a simple prototype consisting of a pair of stacked patch antennas to a more recent prototype (named as Multistatic Array Processing for Radio-wave Imaging Acquisition (MARIA)-4) with a 60-element antenna array [47, 48, 125-130]. One of the earlier prototypes (MARIA-2) that was used to scan patients is
described in [48], [128]. The **MARIA-2** prototype consists of hemispherical antenna array formed around a lower third of a 78-mm radius sphere. The array has 16 antennas that are symmetrically arranged in four rows. An earlier version of this prototype used the staggered antenna arrangement [127].

In the **MARIA-2** prototype, the patient lies in prone position with the breast extended into a conformal antenna array during a breast scan. The prototype uses a multistatic data acquisition approach, where each antenna element is excited in turn using a Vector Network Analyser (VNA) and measurements are recorded at all other antennas. The 16-element array has 16(16 – 1)/2 unique pairs of antennas, resulting in a total of 120 measurements recorded over a frequency band of 4.5 to 9.5 GHz [131]. The frequency-domain measurements are converted to the time-domain using an Inverse Fourier Transform (IFFT) after weighting the frequency-domain data with the spectrum of a modulated Gaussian pulse [131].

The antenna used in this prototype is an aperture stacked-patch antenna. The antenna reported in [132] was modified for the conformal array [128]. The antenna was well matched over the bandwidth of 4.5 to 9 GHz and had good radiation characteristics [128]. The prototype was used in experimental measurements of phantoms as well as patients and initial results were reported in [129].

The 16-element antenna array was further improved to incorporate 31 antenna elements [130] in a plastic shell with openings for the antenna elements (Figure 2.3). The radius of the sphere was increased to 85 mm. The 31 elements of the new prototype (**MARIA-3**) allowed for 461 measurements in approximately 80 seconds. The major change in **MARIA-3** was the use of a wide-slot UWB antenna [133] instead of the stacked-patch antenna used in the previous prototype [128]. While the new antenna had similar bandwidth, it provided the following: more stable radiation pattern across the frequency band of interest, greater than 95% fidelity up to 60° from the antenna boresight and nearly half the size of the previous antenna design [133].

Some of the other improvements included the replacement of the matching liquid with a ceramic shell. **MARIA-2** used a lossy matching liquid with an emulsion of oil and water that was developed to produce the same dielectric properties as
that of normal breast fat \cite{131}. The liquid had a relative dielectric constant of about 10 and an attenuation of 1.2 dB/cm at 6 GHz. A matching liquid was chosen for practical reasons (i.e. only one liquid required for the breast fat and the coupling). However, the matching liquid was partially replaced in the new prototype with a ceramic shell to fill the gap between the antennas and the breast skin. A 1 mm thin layer of matching liquid was still required between antennas and the ceramic shell. The ceramic shell was built using a low loss material with a dielectric constant of 10. Eccostock HiK500F material from the Emmerson Cuming \cite{130} was used to create the ceramic shell. The MARIA-3 prototype (Figure 2.4) was used in experimental studies \cite{107,130} and compared with the previous 16-element MARIA-2 prototype. The new 31-element array provided better imaging results compared to the previous array. The improvements were mainly attributed to both the new wide-slot antenna and the higher spatial diversity of radar data provided by the larger number of antennas. The MARIA-3 prototype was also used in the clinical investigations reported in \cite{134}. 

Figure 2.3: MARIA-3 antenna array with 31 wide-slot antennas (© 2010 IEEE. Reprinted, from \cite{130}).
Figure 2.4: Multistatic Array Processing for Radio-wave Imaging Acquisition (MARIA)-3 with antenna array and scanning hardware (© 2010 IEEE. Reprinted, from [130]).

Figure 2.5: MARIA-4 antenna array with 60 wide-slot antennas (© 2011 IEEE. Reprinted, from [135]).
The prototype was further modified to incorporate 60-elements allowing for 1770 measurements and even higher radar diversity compared to the previous prototype. This newer version MARIA 4 was developed with the aim of improving immunity to clutter and scan times. MARIA 4 used the same wide-slot antenna as MARIA 3. However, the antenna mount, the feed, and the antenna connector were redesigned to fit approximately double the number of antennas in only few millimetre larger Acrylonitrile Butadiene Styrene (ABS) plastic shell than the previous 31-element MARIA prototype. A new switching network was also employed that provided 15 simultaneous measurements. However, it was limited to only 8 GHz in terms of frequency sweep. The choice was justified as the upper 8-10 GHz has limited usage due to high levels of attenuation in breast tissues.

Another important modification in the new 60-element MARIA-4 prototype was the use of a paraffin-based matching liquid with a dielectric constant of 9. The matching liquid was used between the antennas and the ceramic shell to fill...
air gaps. The same liquid was used between the ceramic shell and the breast fitting cups. The filling of air gaps was considered critical to the performance of the prototype. The overall phantom results were similar to the previously reported results \[107, 130\]. The data acquisition time was reduced to 10 seconds compared to the 80-90 seconds scan time of the previous prototype. The clinical investigations \[134\] indicated that slight patient movement during the 90 second scan time was a major contributor to the uncertainties in the measured data. Overall, the new prototype reduced measurement uncertainties by reducing the scan time and improving the repeatability. MARIA-4 was used recently in a clinical trial \[28\] with minor modifications. The measurements were performed in the frequency range of 3-8 GHz and a water-oil-based coupling liquid with dielectric constant 10 was employed. MARIA-4 was used to scan 85 patients and it provided very promising clinical results (sensitivity > 74\%) \[28\].

Another multistatic radar-based breast screening system has been developed at McGill University, Canada \[123\]. The distinctive feature of this prototype is that measurements are acquired in the time-domain, as opposed to the frequency-domain data acquisition using a VNA (in the prototypes described above). The prototype
2. Literature Review

Figure 2.8: Complete prototype at McGill University with examination table and scanning system underneath (© 2016 IEEE. Reprinted, from [27]).

(Figure 2.8) uses a hemispherical bowl-shaped dielectric radome to house a 16-element antenna array (Figure 2.9). The antenna arrangement forms two crosses of 8 elements each, spread over the hemispherical radome. The prototype uses a multistatic data acquisition approach and records a total of 120 measurements in one scan. The prototype consists of a table with a padded bed. The radome is placed underneath the table and the patient lies in the prone position extending the breast into the radome. The major components of the measurement system include an off-the-shelf pulse generator, pulse shaping circuitry, clock and an oscilloscope. The generic pulse produced by the pulse generator is reshaped to limit the frequency content between 2-4 GHz, which was found to be optimal choice for this prototype [136].

The prototype uses an ultrasound gel as a coupling medium between the radome and the breast. The measured dielectric constant of the gel is 68 and the conductivity is 3 S/m [137]. The gel fills the air gaps between the radome and the breast skin in addition to attenuating the undesired multiple reflections. The ultrasound gel is a favourable coupling medium as: it is lossy; it conforms well to the breast skin without the risk of spills (a typical challenge with other liquids); it is already approved for medical use and is readily available at hospitals and clinics.

The antenna used in this prototype is called a Travelling-Wave Tapered and Loaded Transmission-line (TWTLTA) [138]. The antenna has a very large bandwidth
ranging from 2 to 35 GHz, a high radiation efficiency of 39.21% and greater than 95% fidelity. The prototype was developed for breast health monitoring where frequent breast scans can be used to detect “developed” malignancies using differential imaging. The prototype has been used in measurements of experimental phantoms [123, 139]; scanning of the healthy volunteers [140]; monitoring daily tissue changes in patients over a 28-day period [141]; and monitoring 13 healthy volunteers over 8-months period [27, 142].

**Figure 2.9:** Hemispherical radome and antenna elements of McGill University prototype (© 2016 IEEE. Reprinted, from [27]).

**Figure 2.10:** Second generation wearable prototype at McGill University (© 2016 IEEE. Reprinted, from [137]).
The next generation of McGill prototype was made wearable and did not require an exam table \[137\]. The prototype used a fabric bra to house the 16 flexible antennas. The antennas were arranged asymmetrically in the bra in comparison to the symmetric arrangement in the previous prototype. The components of the measurement system remained the same between the two prototypes with the exception of the bra and the antenna. During the scan, the patient wears the bra that closely fits to the breast. Due to the close fit, the antennas that are hosted within the bra come into contact with the breast skin. The contact between the antennas and the breast skin not only eliminates the need of a coupling medium but also reduces the uncertainties in antenna position relative to the skin. The breast positioning relative to the antennas was one of the sources of error in the imaging with the previous prototype.

The wearable prototype used a flexible antenna array (Figure 2.10) that was specifically design for breast imaging \[143\]. The miniaturised monopole antennas were designed to be in contact with the breast. The heterogeneous nature of breast tissues was taken into account while designing the antennas. The antennas were designed for the frequency band of 2-4 GHz. The other components such as pulse generator, pulse shaping circuitry, clock and oscilloscope remained the same as in the previous prototype and described in \[123\]. The wearable prototype is cost effective and offers improved performance compared to the previous prototype. Improved performance was demonstrated by measuring a healthy volunteer on daily basis over a single menstrual cycle \[137\].

The TSAR prototype has been developed at the University of Calgary \[61\]. The prototype (Figure 2.11) has a padded bed with a circular opening that allows the patient to extend the breast into a cylindrical tank placed underneath the bed. The prototype features a monostatic data acquisition system with a UWB antenna that is mounted on a positioning arm. In order to scan a breast, measurements are collected by moving the arm vertically while the entire tank rotates. This results in a cylindrical scan configuration where each measurement is taken by positioning the sensor at a fixed radius from the centre of the tank. The sensor positioning
is controlled by actuating the stepper motors using custom software. The time required to position the sensor and collect the measurements at up to 200 locations around the breast is less than 30 minutes [61].

The UWB antenna used in this prototype is a Balanced Antipodal Vivaldi Antenna with Director (BAVA-D) [144]. The antenna has an additional director to focus the energy into the breast. The antenna has been specifically designed for the TSAR system and offers low distortion, low loss and high directivity. The tank is filled with canola oil to provide coupling between the antenna and the breast. Canola oil has a permittivity of 2.5 and conductivity 0.04 S/m up to 12 GHz. The low permittivity and relatively low-loss of canola oil allows for effective coupling of microwave energy into the breast. The antenna bandwidth is 2.4-18 GHz ($S_{11}$ better than -10 dB) and measurements are acquired using a VNA over the frequency range of 50 MHz to 15 GHz with a port power of -5 dBm. The VNA has a sensitivity of -90 dB and the overall sensitivity of the prototype has been reported between -70 dB to -90 dB [61].

Additionally, the prototype has a laser system mounted on the positioning arm. The collected laser data is used to reconstruct the breast surface, which can facilitate the improvement of reconstructed images. The system also has a digital
camera to monitor the sensor positioning and the breast during the scanning process. The prototype has been used in experimental phantom measurements, volunteer scanning [61] and a small scale patient study that included 9 patients [145].

![Second generation Tissue Sensing Adaptive Radar (TSAR) at the University of Calgary](image)

**Figure 2.12:** Second generation Tissue Sensing Adaptive Radar (TSAR) at the University of Calgary (© 2013 IEEE. Reprinted, from [60]).

The second generation TSAR prototype [60] (Figure 2.12) differs from the first TSAR prototype system [61] in terms of the flexibility in positioning the antenna during the breast scan. The second prototype has two additional degrees of freedom compared to the first prototype and uses the same BAVA-D [144] antenna. The two additional degrees of freedom in antenna movement allow for the positioning of the antenna more closely to the breast skin and the orientation of the antenna orthogonal to the skin at all times. The prototype also has a sophisticated laser system that is used to control the positioning of the antenna during breast scan, in addition to providing data for the skin surface estimation. Hence, the breast can be scanned with a circular scan pattern, a hemispherical scan pattern, and a more adaptive scan pattern specific to the breast. The prototype is controlled by a Graphical User Interface (GUI), allowing the operator to perform the breast scan with ease. The prototype has been used in the measurements of experimental
phantoms and a patient study using this new prototype is currently under-way in the University of Calgary.

![Figure 2.13](image.png)

**Figure 2.13:** Transmission measurement prototype at the University of Calgary (© 2013 IEEE. Reprinted, from [60]). The prototype is used to estimate average dielectric properties of the breast.

In addition to the two TSAR prototypes, the University of Calgary has also developed a transmission measurement prototype (Figure 2.13) to estimate the average dielectric properties of the breast [60]. The average propagation speed of the electromagnetic waves within the breast play a critical role in the image reconstruction process. The average propagation speed is dependent on the dielectric properties of the breast. Therefore, an accurate estimation of the average dielectric properties is vital to the performance of any CMI prototype. Typically, an average value of relative dielectric constant is used [28], [145]. However, an accurately estimated value can provide better imaging [147].

The transmission measurement prototype uses two arrays of Nahanni sensors [148]. Each array consists of 5 elements mounted opposite to each other on two different assemblies. The breast is placed between the two assemblies where the upper assembly is lowered to make contact with the breast skin. While the system
is quite similar to a mammography system in terms of the breast scan, it does not
require the typical breast compression necessary for X-ray mammography.

The Nahanni sensor has been specifically designed for this application. The
sensor consists of a Vivaldi antenna encapsulated into a circular waveguide. The
antenna has a stable directional radiation pattern and wide operational bandwidth
from 1.8 to 12 GHz. The antenna is designed to operate in contact with human
skin and does not require a matching medium. The metallic cylindrical exterior
provides shielding from the multipath interference around the breast [148], [149].

The prototype has been validated using measurements of dielectric slabs and
using deformable experimental breast phantoms [150]. The prototype has also
been used in a small scale patient study of 23 volunteers. The preliminary results
from the patient study showed the consistency between the estimation of relative
dielectric constant over time using this prototype [149].

There are several other prototypes that are currently in pre-clinical stage. These
prototypes have been reviewed in [151].

2.9 Conclusions

In this chapter, a brief overview of the anatomy and physiology of the breast and
the various types of breast cancers are presented. The most recent studies of
cancerous and normal breast tissue have been reviewed and microwave imaging
for the early detection of the breast cancer has been introduced. Furthermore,
al existing artifact removal algorithms, beamforming algorithms, and the clinical
and experimental prototypes for CMI have been reviewed. Comparative studies
of various beamforming algorithms have also been described. In addition, the
most commonly used MRI-based numerical breast phantoms developed for the
evaluation of the microwave imaging algorithms have been introduced. Finally, a
brief overview of clinical prototypes developed for radar-based microwave breast
imaging has been presented.

Most artifact removal algorithms have shown promising results in specific
scenarios but they are based on simplifying assumptions about the degree of
commonality in the artifact across all channels. However, several real-world clinical scenarios could result in greater variation in the early-stage artifact, making the artifact removal process much more difficult. Despite the importance of artifact removal, no comprehensive comparison of artifact removal algorithms has been reported previously. Most of the existing artifact removal algorithms reported in the literature have been applied to monostatic data and effective multistatic artifact removal algorithms need to be developed.

**DI** beamformers perform well in simple homogeneous scenarios. However, the performance of **DI** beamformers is greatly reduced in dielectrically heterogeneous breast due to presence of fibroglandular tissues. **DA** beamformers provide high resolution images with good clutter suppression but they are computationally intensive, sensitive to steering vector inaccuracies and pre-processing errors such as residual early-time artifacts. Existing studies comparing the performance of imaging algorithms have either used anatomically and dielectrically inaccurate breast phantoms or have evaluated only a selected subset of the imaging algorithms. The literature particularly lacks a comprehensive study on the evaluation of the various **DI** and **DA** beamforming algorithms using experimental and patient data.

The review presented in this chapter provides motivation for the evaluation of artifact removal algorithms, and for the development of much improved artifact removal algorithms, which can effectively reduce the early-time artifact. An improved artifact removal algorithm should be able to effectively reduce the early-time artifact in monostatic as well as multistatic systems, and must be robust to experimental noise and scan configuration used in various experimental and clinical breast imaging prototypes. Further, the performance of the various imaging algorithms in realistic clinical scenarios needs to be investigated. The rest of the thesis addresses these questions.
3 Artifact Removal Algorithms

3.1 Introduction

One of the most important signal processing components of any CMI system for breast cancer detection is the early-time artifact removal algorithm. The early-time artifact is typically composed of reflections from several interfaces. In a typical microwave breast imaging system, the illuminating electromagnetic wave travels through the immersion liquid and skin before reaching the interior of the breast. The difference in the permittivity of the immersion liquid, the skin and the interior of the breast results in a reflection at each interface between the antenna, the immersion liquid and the breast skin surface.

The first reflection is generated at the antenna-immersion interface and is not expected to be significant, as the antenna is typically matched to the immersion medium. The most significant reflections result from the immersion-skin interface and the skin-adipose tissue interface. These interfaces are located closer to the antenna and therefore reflections appear in the early-time of the backscattered signal. The reflections from the interior of the breast appear later in time. The early-time artifact is the combination of these reflections and of any antenna reverberation present.
The early-time artifact is typically several orders of magnitude larger than the reflections from healthy or malignant tissues (tumours) present within the breast. If the artifact is not removed effectively, it could easily mask tumours present within the breast, or result in false-positives.

Several algorithms \[34\]–\[38], \[47\], \[152\], \[153\] have been proposed in the literature to remove the early-time artifact. As mentioned previously that many of these existing artifact removal algorithms are based on simplifying assumptions about the degree of commonality in the artifact across all channels. However, several real-world clinical scenarios could result in greater variation in the early-stage artifact, making the artifact removal process much more difficult.

Despite the importance of artifact removal, and the development of a number of algorithms, no comprehensive comparison of early-time artifact removal algorithms for microwave breast imaging has been performed previously. This chapter presents a comparison of a wide-range of existing artifact removal algorithms for microwave breast imaging, along with an algorithm adapted from the GPR applications. The algorithms are implemented and applied to MRI-derived 2D numerical breast phantoms. The results are compared across a range of appropriate performance metrics. The work described in this chapter is published in [154].

The remainder of the chapter is organised as follows: Section 3.2 describes each artifact removal algorithm in detail; Section 3.3 describes the numerical breast phantoms and performance metrics used to evaluate the algorithms; and Section 3.4 describes the various tests applied to the artifact removal algorithms and the corresponding results. Finally, the conclusions are presented in Section 3.5.

### 3.2 Artifact Removal Algorithms

In this section, each artifact removal algorithm is described in detail. The following artifact removal algorithms have previously been applied to signals from microwave breast imaging systems:

- Average Subtraction \[34\]:
3. Artifact Removal Algorithms

- Rotation Subtraction [47];
- Adaptive Filtering [35], [36];
- Entropy-based Window Design [37];
- Frequency-domain Pole Splitting [38].

Additionally, an algorithm based on the statistical signal processing techniques, which is adapted from GPR applications, is also considered in this study.

- Singular Value Decomposition (SVD) [153].

3.2.1 Average Subtraction

In the Average Subtraction, the artifact is estimated as an average of the signal recorded at each channel. The artifact is removed by subtracting this estimated artifact from each received signal:

\[ s_i[n] = b_i[n] - \frac{1}{N} \sum_{i=1}^{N} b_i[n] \]  

(3.1)

where \( b_i[n] \) is the vector containing the signal recorded at channel \( n \), \( N \) is the total number of channels and \( s_i[n] \) is the artifact-free signal.

3.2.2 Rotation Subtraction

The Rotation Subtraction method was proposed by Klemm et al. [47] and requires two separate radar measurements. The first set of measurements is recorded with the circular antenna array surrounding the breast in one position, and a second set of signals is recorded after the antenna array has been rotated at a certain angle in the horizontal plane around the vertical axis, as follows:

\[ s_i[n] = b_i[n] - b_r[n] \]  

(3.2)

where \( b_r[n] \) is the vector containing the signals recorded after the antenna array has been rotated.
3.2.3 Adaptive Filtering

In this section, two types of adaptive filtering methods are described.

3.2.3.1 Wiener Filter

The Wiener Filter artifact removal algorithm was originally proposed by Bond et al. [35]. This algorithm improves on the simple Average Subtraction method by compensating for channel-to-channel variation in artifacts due to local variation in skin thickness, breast heterogeneity and differences in antenna-skin distances.

In this method, the artifact in each channel is estimated as a filtered combination of the signals in all other channels. The estimated artifact signal for channel $i$ is then subtracted from the received signal as follows:

$$s_i[n] = b_i[n] - q^T b_{PN}[n]$$  \hspace{1cm} (3.3)

where $b_i[n]$ is the vector containing the signal received at channel $i$, $b_{PN}[n]$ is a vector calculated from all other channels except $i$, and $q$ is the vector of filter weights.

The filter weights are chosen to minimise the residual signal mean-squared error over the portion of the signal dominated by the artifact. For example, in order to remove the artifact from channel 1, a $(2J + 1) \times 1$ vector of time samples in the $k^{th}$ channel is defined as:

$$b_k[n] = [b_k[n - J], ..., b_k[n], ..., b_k[n + J]]^T, 2 \leq k \leq N$$  \hspace{1cm} (3.4)

where $J$ is the number of samples on either side of $n^{th}$ time sample, and $2J + 1$ is the length of the averaging window centred on $n$. The samples of $b_k[n]$ for channels 2 through $N$ are concatenated into a vector $b_{2N}[n]$ as:

$$b_{2N}[n] = [b_2^T[n], b_3^T[n], ..., b_N^T[n]]^T$$  \hspace{1cm} (3.5)

The filter weight vector $q$ is then calculated as:

$$q = \arg \min_q \sum_{n=n_o}^{n_o+m-1} |b_1[n] - q^T b_{2N}[n]|^2$$  \hspace{1cm} (3.6)

where the time-window $n = n_o$ to $n = n_o + m - 1$ represents the initial portion of the signal dominated by the artifact.
3. Artifact Removal Algorithms

3.2.3.2 Recursive Least Squares Filter

The RLS algorithm was proposed for artifact removal by Sill et al. [36]. The RLS is an adaptive filtering algorithm that recursively computes and updates the filter weights. This is in contrast to the Wiener Filter method which shifts constant weight vectors through the selected artifact window.

Let $u_r$ be the $1 \times N$ vector containing $N$ time samples of the desired signal at channel $r$ and $u = [u_{r+1}, u_{r+2}, ..., u_{r+M}]^T$ is the $M \times N$ matrix containing signals at the remaining $M$ channels. Define $M \times 1$ weight vector at time $n$ as:

$$w(n) = [w_{r+1}(n), w_{r+2}(n), ..., w_{r+M}(n)]^T$$  \hspace{1cm} (3.7)

The desired signal $d(i) = u_r$ can then be approximated as:

$$\hat{d}(i) = w^T(n)u(i)$$  \hspace{1cm} (3.8)

and the error is calculated as:

$$e(i) = d(i) - \hat{d}(i)$$  \hspace{1cm} (3.9)

At time $n$, the sum of squared error is defined as:

$$J(n) = \sum_{i=1}^{n} \lambda^{n-i} |e(i)|^2$$  \hspace{1cm} (3.10)

where $n$ is the current sample number and $0 < \lambda \leq 1$ is the forgetting factor that exponentially assigns less weight to previous error samples. The minimisation of the mean squared error with respect to $w(n)$ results in the Wiener-Hopf equation, which can be recursively solved using a standard brute force approach. Further details on the specific implementation can be found in [36].

The RLS algorithm is used in conjunction with Woody-Averaging [152]. The RLS algorithm is applied to the initial portion of signal, which is dominated by the artifact, and Woody averaging is applied to the remaining portion of the signal. This total estimated signal is then subtracted from the target signal. The artifact-dominated portion of the signal is selected empirically.
3. Artifact Removal Algorithms

3.2.4 Singular Value Decomposition

SVD has been previously used for clutter reduction in GPR [155] and for through-wall imaging [153]. SVD is used to decompose the received signals into the tumour and artifact subspaces. The components containing the tumour are selected, and the artifact components are discarded.

The received signals are represented by a $M \times N$ matrix $X$, where $N$ is the total number of time samples and $M$ is the total number of channels. A singular value decomposition of $X$ is given as:

$$X = USV^T$$

where $U = [u_1, u_2, ..., u_M]$ and $V = [v_1, v_2, ..., v_N]$ (having dimensions $M \times M$ and $N \times N$) are left and right unitary matrices respectively. Let $S = diag(\sigma_1, \sigma_2, ..., \sigma_M)$ with $\sigma_1 \geq \sigma_2 \geq ... \geq \sigma_M \geq 0$ be the singular values of $X$. The SVD of $X$ can then be written as:

$$X = \sum_{i=1}^{M} \sigma_i u_i v_i^T$$

$$X = E_1 + E_2 + E_3 + ... + E_N$$

where $E_i$ is the $i^{th}$ eigenvalue of the mode of $X$ having the same dimensions as of $X$.

$X$ can be decomposed into two subspaces as:

$$X = \sum_{i=1}^{k} \sigma_i u_i v_i^T + \sum_{i=k+1}^{M} \sigma_i u_i v_i^T$$

where the first $k$ singular values belong to the artifacts and the remaining values belong to the tumour response.

Verma et al. [153] proposed that the first spectral component $k = 1$ in (3.14) represents the clutter. However, in this study the experimental data suggested that the clutter subspace is composed of more than one spectral component. Therefore, the difference of singular values $\sigma_i - \sigma_{i+1}$ is used to estimate the optimal value of $k$:

$$k = \arg \max_i (\sigma_i - \sigma_{i+1})$$
3.2.5 Entropy-based Time-Window

The EBTW artifact removal algorithm was proposed by Zhi et al. [37]. The algorithm is based on the assumption that the artifacts in the received signals are highly similar across all channels, which is not the case for the tumour response, as it is delayed and attenuated differently in each channel.

Entropy is a measure of the variation of the signal, where entropy is inversely proportional to the amount of variation. Therefore, a larger value of entropy is obtained from similar artifacts in the early portion of the radar signals. Conversely, the tumour reflections result in a much lower entropy value. A window function can be defined based on the entropy values, while the artifacts can be removed by multiplying the window function with the received signal at each channel.

Each received radar signal is normalised as:

\[ p_i[n] = \frac{\|b_i[n]\|^2}{\sum_{i=1}^{M} \|b_i[n]\|^2} \]  \hspace{1cm} (3.16)

where \( b_i[n] \) is the received signal at \( i^{th} \) channel and \( M \) is the total number of channels.

From (3.16), \( \{p_1[n], p_2[n], ... p_M[n]\} \) provides the probability distribution of the energy across each antenna at a time instant \( n \). Equation (3.16) also satisfies the essential criteria of a Probability Density Function (PDF), i.e. \( p_i[n] \geq 0 \) and \( \sum_{i=1}^{M} p_i[n] = 1 \). The given PDF can be interpreted as the energy density in the antenna domain as it provides the energy per antenna at a given time instant.

The entropy can be used to characterise the most probable distribution of the energy across all channels. The uniform distribution of energy across all channels in the early-time portion of the signals will result in the maximum entropy. However, variations in the late-time part will result in lower entropy.

The \( \alpha \)-th order Renyi entropy at time sample \( n \) is defined as:

\[ H_{\alpha}[n] = \frac{1}{1-\alpha} \log \left( \sum_{i=1}^{M} (p_i[n])^\alpha \right) \]  \hspace{1cm} (3.17)

where \( \alpha \) is real-positive and the entropy varies from zero for certain event to \( \log \) \( M \) for uniform distribution.
For a finite dimensional signal $b_i[n]$, a theoretical dimension \([156]\) can be defined as $D[n] = e^{H^*_\alpha[n]}$, where $H^*_\alpha[n]$ is the smoothed entropy, given as:

$$H^*_\alpha[n] = \frac{1}{M} \sum_{k=n}^{k=n+M} H_\alpha[k] \quad (3.18)$$

The $D[n]$ rearranges the entropy such that $1 \leq D[n] \leq M$. The time-window function is obtained by comparing the theoretical dimension with a specific threshold as follows:

$$W[n] = \begin{cases} 0, & e^{H^*_\alpha[n]} > N_0 \\ 1, & otherwise \end{cases} \quad (3.19)$$

where $1 < N_0 < M$. The artifact removed signal can then be obtained by multiplying the time-window function with the received signal at the $i^{th}$ channel:

$$s_i[n] = W[n]b_i[n] \quad (3.20)$$

### 3.2.6 Frequency Domain Pole Splitting

The Frequency Domain Pole Splitting artifact removal algorithm was originally proposed by Maskooki et al. \([38]\). The principle of this algorithm is to represent the frequency response of each received radar signal as a sum of complex exponentials, where each complex exponential represents a pole of the system and each pole corresponds to a specific scatterer in the view of the antenna. The artifacts can then be removed by removing the pole corresponding to the strongest scatterers from the frequency response.

The frequency response of each received signal can be decomposed into its poles as follows:

$$y(k) = \sum_{p=1}^{N} a_p e^{(\alpha_p+j\frac{2\pi}{R_p})k\Delta f} \quad (3.21)$$

where $N$ is the total number of scatterers or poles of the system, $a_p$ is the constant coefficient, $\alpha_p$ is the frequency decay/growth factor, $R_p$ is the range of the $p^{th}$ scatterer and $\Delta f$ is frequency step size.

The received signals are first converted to the frequency-domain using the Fast Fourier Transform (FFT) algorithm. These frequency-domain signals are
then processed using the linear system identification method [157] to estimate the frequency model given in (3.21) [158]. The frequency-domain signal is arranged in the form of a Hankel matrix as follows:

\[
H = \begin{bmatrix}
y_i(1) & \cdots & y_i(L) \\
\vdots & \ddots & \vdots \\
y_i(N - L + 1) & \cdots & y_i(N)
\end{bmatrix}
\] (3.22)

where \( y_i(n) \) is the \( n^{th} \) frequency sample at channel \( i \) and \( N \) is the total number of frequency samples.

The Hankel matrix is then decomposed into the signal plus noise and noise only subspaces using SVD. The noise subspace is then removed. \( H \) can be approximated as:

\[
\tilde{H} = U_{sn} \Sigma V_{sn}^* 
\] (3.23)

where \( U_{sn} \) is the left unitary matrix of the signal-plus-noise subspace, \( V_{sn}^* \) is the right unitary matrix of signal plus noise subspace, and \( \Sigma \) contains the dominant singular values of \( H \) in descending order, with (*) denoting conjugate transpose. The criterion to separate the two subspaces is the Akaike Information Criterion [159].

The approximated \( H \) from (3.23) is used to estimate the \( a_p, \alpha_p \) and \( R_p \). Using these parameters in (3.21), the frequency-domain signal is reconstructed. The parameter \( a_p \) is directly related to the amplitude of the pulses in the time-domain signal. Since the magnitude of the tumour pulse is much smaller than the artifact, a threshold is used to remove the poles with dominant \( a_p \) values during the reconstruction of the frequency response. Hence, the reconstructed signal will only contain the tumour response. This reconstructed signal is then converted into the time-domain using IFFT.

### 3.3 Simulations and Performance Metrics

In this section, both the numerical breast phantoms and the performance metrics used to evaluate and compare the artifact removal algorithms are described.
3.3.1 Numerical Breast Phantoms

The numerical breast models used in this study are derived from MRI-based breast phantoms, taken from the UWCEM breast phantom repository, which has been detailed in Section 2.7. Each breast model is surrounded by an array of 12 antennas arranged in a circular configuration around the circumference of the breast.

The elements of the antenna array are modelled as electric-current sources, immersed in a synthetic material matching the dielectric properties of adipose tissue. The entire system is simulated using the FDTD method in a simulation grid of 95 mm x 120 mm with the grid resolution of 1 mm. A location within the breast is described in terms of (X mm, Y mm).

Two breast models have been considered in this study. The FDTD model shown in Figure 3.1(b) is a dielectrically homogeneous model, composed of adipose tissues only whereas the model shown in Figure 3.1(a) is heterogeneous with a region of fibroglandular tissue. A 7.5 mm diameter tumour is located at two different positions in each breast model: ((59 mm, 72 mm) and (59 mm, 88 mm)).

The illuminating signal is a 150-ps differentiated Gaussian pulse, with a centre frequency of 7.5 GHz and a -3dB bandwidth of 9 GHz as previously used in [114]. Before further processing, the acquired backscattered recorded signals are downsampled from 1200 GHz to 50 GHz.

3.3.2 Performance Metrics

Four metrics are used to evaluate the artifact removal algorithms. The Peak-to-Peak Response Ratio (PPRR) and the Correlation Measure (CM) are applied to the raw radar signals, whereas the Signal-to-Mean Ratio (SMR) and Structure Similarity Index Metrics (SSIM) [160] are calculated from the resultant beamformed images. These aforementioned metrics will be described in the following subsections.
3. Artifact Removal Algorithms

Figure 3.1: Finite-Difference Time Domain (FDTD) models of the breast showing the permittivity at 7.5 GHz and the antenna locations shown as small cyan dots on the skin: (a) homogeneous breast, (b) heterogeneous breast. The corresponding beamformed images obtained after the ideal artifact removal: (c) homogeneous breast, (d) heterogeneous breast.

3.3.2.1 Peak-to-Peak Response Ratio

The PPRR is the ratio of the peak-to-peak magnitude of the radar signal following and prior to artifact removal. The PPRR measures how much of the artifact has been removed from a particular channel.

3.3.2.2 Correlation Measure

The CM is used to measure the ability of the artifact removal algorithm to preserve the tumour response. This is computed by correlating the ideal tumour response with the tumour response obtained for a particular artifact removal algorithm.
3. Artifact Removal Algorithms

3.3.2.3 Signal-to-Mean Ratio

The SMR is a measure of the quality of the beamformed image, after the application of a particular artifact removal algorithm. It is defined as the ratio of peak tumour response to the average response in the image.

3.3.2.4 Structural Similarity Index

The SSIM is an image quality metric that indicates the similarity between two images [160]. The SSIM outputs values in the range 0-1, where 1 indicates that the test and the reference image are identical. An ideal reference image is generated using an ideal artifact removal algorithm. SSIM is calculated as follows:

$$
SSIM = \frac{(2 \times \bar{x} \times \bar{y} + C1)(2 \times \sigma_{xy} + C2)}{(\sigma_x^2 + \sigma_y^2 + C2) \times (\bar{x}^2 + \bar{y}^2 + C1)}
$$

where \(x\) is the reference image, \(y\) is the test image, \(\bar{x}\) and \(\bar{y}\) represent the corresponding mean, \(\sigma_x\) and \(\sigma_y\) represent the corresponding variance and \(\sigma_{xy}\) is the covariance of the reference and test image. \(C1\) and \(C2\) are small constants [160].

3.4 Results

In this section, results obtained after application of artifact removal algorithms are discussed.

Table 3.1 illustrates the overall performance of each artifact removal algorithm in terms of PPRR and CM, while Table 3.2 presents their respective performances in terms of the quality of the resultant breast images (SMR and SSIM). Figure 3.2 shows the time-domain plots and images for each algorithm. From Table 3.1, the Average Subtraction and Rotation Subtraction algorithms fail to effectively remove the artifact, as indicated by the fact that these algorithms have the lowest PPRR values. The PPRR and CM values for the RLS algorithm suggest that while the algorithm removes the majority of the artifact, the tumour response suffers significant distortion. Similarly, the SVD algorithm also significantly reduces the artifact but introduces distortion in the tumour response. The EBTW performed quite well as evidenced by both the PPRR and CM values. The Frequency Domain
Table 3.1: Performance metrics for artifact removed signals

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>PPRR</th>
<th>Correlation Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal</td>
<td>-131.39</td>
<td>1.00</td>
</tr>
<tr>
<td>Rotation Subtraction</td>
<td>-30.73</td>
<td>0.14</td>
</tr>
<tr>
<td>Average Subtraction</td>
<td>-38.18</td>
<td>0.10</td>
</tr>
<tr>
<td>Wiener Filter</td>
<td>-126.38</td>
<td>0.66</td>
</tr>
<tr>
<td>RLS</td>
<td>-83.61</td>
<td>0.37</td>
</tr>
<tr>
<td>SVD</td>
<td>-123.19</td>
<td>0.45</td>
</tr>
<tr>
<td>EBTW</td>
<td>-121.88</td>
<td>0.60</td>
</tr>
<tr>
<td>Frequency Domain</td>
<td>-135.43</td>
<td>0.37</td>
</tr>
</tbody>
</table>

Table 3.2: Performance metrics for beamformed images

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>SSIM</th>
<th>SMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal</td>
<td>1.00</td>
<td>30.32</td>
</tr>
<tr>
<td>Rotation Subtraction</td>
<td>0.05</td>
<td>15.00</td>
</tr>
<tr>
<td>Average Subtraction</td>
<td>0.05</td>
<td>18.38</td>
</tr>
<tr>
<td>Wiener Filter</td>
<td>0.84</td>
<td>25.59</td>
</tr>
<tr>
<td>RLS</td>
<td>0.80</td>
<td>25.88</td>
</tr>
<tr>
<td>SVD</td>
<td>0.72</td>
<td>25.36</td>
</tr>
<tr>
<td>EBTW</td>
<td>0.77</td>
<td>24.54</td>
</tr>
<tr>
<td>Frequency Domain</td>
<td>0.60</td>
<td>23.07</td>
</tr>
</tbody>
</table>

Pole Splitting algorithm has better PPRR value than all algorithms but a very low CM value of 0.37, again indicating a distortion of the tumour response. Finally, the Weiner Filter yields a smaller PPRR value and has the highest CM value. This suggests that the Wiener Filter not only removes almost all the artifact, but it also preserves the tumour response.

Similar trends can be seen in terms of the imaging performance metrics shown in Table 3.2. The Wiener Filter algorithm produces the highest SSIM value indicating that it generated the best beamformed image. SSIM values for RLS and Entropy based Window algorithms are also quite close to the ideal image. The RLS algorithm has a quite high SSIM value despite its poor CM value, due to the residual artifacts being compensated for by the beamformer. A more detailed analysis of the performance of each algorithm is now provided.
3. Artifact Removal Algorithms

Figure 3.2: The first column shows the artifact removed time-domain signals, where the solid blue line represents the ideal tumour signal obtained after ideal artifact removal and the red dotted line shows the signal obtained after the application of a real artifact removal algorithm. The second column shows images of the homogeneous breast and the third column shows the images of the heterogeneous breast obtained after the application of each artifact removal algorithm. The first row shows the results of the Rotation Subtraction algorithm. The second row shows the results of the Average Subtraction algorithm. The third row shows the results of the Wiener Filter algorithm. The fourth row shows the results of the Recursive Least Squares (RLS)-Woody combination. The fifth row shows the results of the Singular Value Decomposition (SVD) algorithm. The sixth row shows the results of the Entropy-based Time Window (EBTW) algorithm. The seventh row shows the results of the Frequency-domain pole splitting algorithm.
3.4.1 Rotation Subtraction

Figure 3.2(a) shows the radar signal derived from the homogeneous model after processing by the Rotation Subtraction artifact removal algorithm, and the same signal following the application of an ideal artifact removal algorithm. The solid line shows the ideal signal and the dashed line is the tumour response signal after the Rotation Subtraction algorithm has been applied. The results are obtained after the antenna array has been rotated by $30^\circ$. It can be seen that the Rotation Subtraction algorithm has failed to completely remove the artifact. This is due to the variation in the artifact at different locations across the breast.

Figure 3.2(b-c) shows the images generated from the resultant artifact removed signals. Maximum energy concentration is at the antenna locations due
3. Artifact Removal Algorithms

3.4.2 Average Subtraction

Figure 3.2(d-f) illustrate the performance of the simple Average Subtraction artifact removal algorithm. The signals obtained following the application of the Average Subtraction algorithm still have strong artifacts contained in the early-stage response.

The residual artifact can be attributed to the fact that the Average Subtraction algorithm assumes that the early-stage artifact will be same across all channels, and also that the averaging process will correctly estimate the artifact. However, the artifact typically varies between channels due to local variations in skin thickness and differences in the antenna-skin distance. Due to the presence of strong artifacts in the resultant image, the tumour cannot be detected in the breast images, as shown in Figure 3.2(e-f).

3.4.3 Wiener Filter

The Wiener Filter artifact removal algorithm is applied to the radar signals with filter parameters \( J = 3, p = 12, m = 23 \). The results are plotted in Figure 3.2(g-i). These results demonstrate that the artifacts have been significantly reduced when compared to the Rotation Subtraction and Average Subtraction algorithms.

The Wiener Filter algorithm has performed equally well for both tissue models considered in this study. Figure 3.2(g) show that the Wiener Filter algorithm has not been able to completely eliminate the skin artifacts. However, the artifacts have been significantly reduced with very little distortion being introduced in to the tumour response.

The resultant beamformed images are shown in Figure 3.2(h-i). The images closely resemble the ideal images shown in Figure 3.1(c-d) and both tumours can be easily detected.
3.4.4 Recursive Least Squares Filter

The RLS Filter combined with the Woody averaging artifact removal algorithm is applied to the received signals and the results plotted in Figure 3.2(j-l). These results demonstrate that the RLS-woody combination has reduced the artifacts but some residual artifacts still remain. These residual artifacts include a peak in the early-time response that is actually greater in magnitude than the tumour response. Furthermore, the averaging of the late-time signal introduces distortion in the tumour response, which can reduce the quality of the resultant beamformed images. These images are shown in Figure 3.2(k-l).

3.4.5 Singular Value Decomposition

Figure 3.2(m-r) show the results obtained by removing the early-stage artifact using SVD. It can be seen that the algorithm has reduced the artifact but has failed to completely remove the artifact. The algorithm has also significantly distorted the tumour response. This distortion effect is clearly visible in the beamformed images, where the tumour energy appears relatively dispersed (i.e. incoherent addition of the radar signals at the tumour location).

3.4.6 Entropy-based Time-Window

In the case of the EBTW algorithm, the third order entropy with $\alpha = 3$ is computed for the received radar signals. The artifact has a large entropy compared to the late-time tumour response. The threshold value is set to half of the number of channels (i.e. $N_0 = 6$) in order to design the time-window (which is then multiplied with the radar signals across all channels).

Figure 3.2(p) shows that the artifacts have been almost completely removed by this algorithm while portions of artifacts close to the tumour response were not removed. This is due to the fact that the algorithm incorrectly estimates the artifact as part of the tumour response when the residual artifacts are very close in magnitude to tumour response. Since the algorithm is only applied to the early-time portion of the signal, no distortion of the tumour response occurs.
3. Artifact Removal Algorithms

Images obtained from signals after the \text{EBTW} algorithm are applied are shown in Figure 3.2(p-r).

3.4.7 Frequency Domain Pole Splitting

The Frequency Domain Pole Splitting algorithm is applied to the radar signals and the results are shown in Figure 3.2(s-u). In order to remove the dominant poles, the threshold is set to higher than the ratio of peak tumour to the artifact response multiplied by the maximum $a_p$ values, as proposed by Maskooki [38]. The poles with $a_p$ values larger than this threshold are then removed. The algorithm is quite effective in removing artifacts, but the distortion in the tumour response is much greater compared to all other algorithms, resulting in relatively poor images as shown in Figure 3.2(s-u).

Residual artifacts and distortion are much more visible in the heterogeneous model. The tumour can be detected in the homogeneous model as shown in Figure 3.2(t) but it is obscured by clutter in the heterogeneous model as shown in Figure 3.2(u).

3.5 Conclusions

In this chapter, an extensive range of artifact removal algorithms developed originally for both microwave breast imaging and \text{GPR} applications have been described and compared.

Results obtained from this study indicate that the Rotation Subtraction and Average Subtraction artifact removal algorithms fail to effectively remove the early-stage artifact. This is primarily due to local variations in skin thickness and differences in the antenna-skin distance. Conversely, adaptive filtering algorithms perform well when applied to the portion of signal dominated by artifacts and are more robust to variations in the early-stage artifact. The Frequency Domain Pole Splitting and the \text{SVD} method significantly reduce the artifact but also introduce considerable distortion in the tumour response. The \text{EBTW} algorithm completely
removes the part of signal estimated to contain the artifacts. However it often fails to accurately estimate the exact portion of signal containing the artifact. Overall, the Wiener Filter algorithm effectively reduced the artifacts, while preserving the tumour response. However, the artifact-dominant window was chosen empirically to optimise the filter weights. The Wiener Filter algorithm can be improved by combining it with an artifact-dominant window estimation algorithm.

In the following chapter, a hybrid artifact removal algorithm will be described. The hybrid artifact removal algorithm will combine an improved EBTW algorithm and Wiener Filter algorithm to remove the artifact without introducing significant distortion into the tumour response.
4

Hybrid Artifact Removal Algorithm

4.1 Introduction

In the previous chapter, the efficacy of various early-time artifact removal algorithms for CMI was investigated. The algorithms were applied to 2D numerical breast phantoms and the advantages and limitations of each algorithm were discussed.

The study concluded that the filter-based algorithms [35], [36], in particular the Weiner Filter algorithm [35] effectively reduces the early-time artifacts provided that the time-window containing the artifacts was known a-priori. The EBTW algorithm was shown to be an effective method for estimating the artifact-dominant portion of the signals but had limited accuracy in determining the artifact-dominant time-window size.

The study also highlighted the fact that several factors determine the effectiveness of an early-stage artifact removal algorithm for the detection of breast cancer using CMI. These factors include: the ability to select the correct time-window containing the artifact; the ability to remove the artifact while being robust to normal variances; and the ability to effectively preserve the tumour response in the resultant signal. Very few, if any, of the existing artifact removal algorithms incorporated all of these qualities.
4. Hybrid Artifact Removal Algorithm

In this chapter, a novel hybrid artifact removal algorithm for microwave breast imaging applications is presented. The proposed hybrid artifact removal algorithm combines the best attributes of the EBTW algorithm \cite{37} and the Wiener Filter algorithm \cite{35} to effectively remove the early-stage artifact while preserving the tumour response. The algorithm is evaluated using anatomically and dielectrically accurate 3D numerical breast phantoms (in comparison with the 2D dielectrically homogeneous numerical breast model originally used by Zhi et al. \cite{37}). The proposed algorithm shows an obvious improvement compared to the original EBTW algorithm across a range of appropriate metrics. The work described in this chapter is published in \cite{161}.

The remainder of the chapter is organised as follows: Section 4.2 describes the proposed artifact removal algorithm in detail; Section 4.3 describes the 3D numerical breast phantom used to evaluate the algorithm; and Section 4.4 details the various tests applied to the artifact removal algorithm and the corresponding results. Finally, the conclusions are presented in Section 4.5.

4.2 Artifact-Dominant Window Selection for Adaptive Artifact Filtering

In this section, the development of the improved EBTW algorithm and the integration of the improved EBTW algorithm, with the Weiner Filter algorithm, are described in detail.

The first step of the proposed artifact removal algorithm is to automatically select the artifact-dominated portion of backscattered signals based on entropy values. In order to better select the artifact-dominant time-window, the proposed algorithm improves upon the original EBTW artifact removal algorithm proposed by Zhi et al. \cite{37}.

While Zhi’s algorithm is effective in removing the artifact, it often fails to correctly estimate the exact portion of the signal containing the artifact. It also tends to remove part of tumour response, when the early-time artifact and tumour responses overlap in time. Therefore, an improved algorithm was developed to
more accurately estimate the artifact-dominated portion of the signal. The EBTW algorithm is based on the assumption that the artifacts in the received signals are similar across all channels, unlike the case for the tumour response in real breast imaging scenarios (the tumour response is delayed and attenuated differently due to variations in the tissue structures at each channel).

A larger value of entropy is obtained from similar artifacts in the early portion of the radar signal. Conversely, the tumour reflections result in a much lower entropy value. A window function estimated to contain the artifact can be defined based on the entropy values. The detailed formulation of the EBTW algorithm is described in Section 3.2. In summary, a PDF is created by normalising all received radar signals. The PDF is used to define the $\alpha$-order Renyi entropy for each time sample $n$ that varies from zero for certain events (variations), to $\log M$ for uniform distributions (similarities). A smoothing window is applied to the entropy and a theoretical dimension function $D[n]$ is defined to rearrange the entropy such that $1 \leq D[n] \leq M$.

Zhi et al. [37] proposed that the time-window function can then be obtained by comparing the theoretical dimension with a specific threshold as follows:

$$W_l[n] = \begin{cases} 0, & D_l[n] > N_0 \\ 1, & otherwise \end{cases}$$

(4.1)

where $1 < N_0 < M$. The artifact removed signals can then be obtained by multiplying the time-window function with the received signal at each channel. However, empirical tests have shown that the window function given in (4.1) does not always yield the best artifact window in terms of completely locating the artifact.

Therefore, an alternative method to design the artifact-dominant time-window is proposed. Firstly, the maxima of the function $D_l[n]$ is computed. The first maximum represents the point in time where signals across all channels have the highest similarity, and the adjacent local minimum indicates the maximum variation. The highly similar part of the signals is assumed to be the artifact and the artifact-dominant time-window is then defined from the start of the signal to the local minima on the theoretical dimension curve.
Once the artifact dominated window has been defined, the next step is to apply the Wiener Filter algorithm \cite{35} to each signal. The computed entropy-based time-window is used to optimise the filter coefficients. Using the Wiener Filter algorithm detailed in Section \ref{sec:filter_algorithm}, the artifact in each channel is estimated as a filtered combination of the signals in all other channels. The estimated artifact signal for channel $i$ is then subtracted from the received signal at channel $i$ as follows:

$$s_i[n] = b_i[n] - q^T b_{PN}[n]$$

(4.2)

where $b_i[n]$ is the vector containing the signal received at channel $i$, $b_{PN}[n]$ is a vector calculated from all other channels (except channel $i$) as described in Section \ref{sec:filter_algorithm} and $q$ is the vector of filter weights. The filter weights are chosen to minimise the residual signal mean-squared error over the portion of the signal dominated by the artifact.

The filter weight vector $q$ for each signal is then calculated as:

$$q = \arg\min_q \sum_{n=n_o}^{n_o+m-1} |b_i[n] - q^T b_{PN}[n]|^2$$

(4.3)

where $n_o$ represents the start of the signal and $m$ is the length of the artifact-dominant portion of the signal, which is estimated using the entropy method described previously.

4.3 Simulations and Performance Metrics

In this section, the development of the numerical breast phantoms, simulation-setup and performance metrics used to evaluate the proposed algorithm, are described.

4.3.1 Numerical Breast Phantoms

An accurate 3D numerical breast phantom must incorporate the appropriate geometrical properties of the breast, the heterogeneity, and spatial distribution of the different constituent tissues within the breast. Similar to the previous chapter, the breast phantoms considered in this study are also derived from the MRI-based breast phantoms available from the UWCEM breast phantoms repository \cite{121}. However, the breast phantoms simulated in this study are 3D as opposed to 2D.
breast phantoms used in the previous chapter. The dielectric properties and the Debye parameters used in the models are detailed in Section 2.7.

![Figure 4.1: Three-dimensional Finite-Difference Time Domain (FDTD) breast model and antenna configuration.](image)

Two concentric rings of Hertzian dipole antennas (each containing 25 antenna elements) are positioned around the breast as shown in Figure 4.1. The antenna elements are immersed in a coupling medium which matches the dielectric properties of adipose tissue. The entire simulation space is 150 mm x 150 mm x 150 mm, with a grid resolution of 1 mm. Each location within the breast is described in terms of (X mm, Y mm, Z mm). The simulations are performed using the FDTD method.

For completeness, three breast models have been considered in this study: a homogeneous breast model composed of adipose breast tissues only; a heterogeneous model with heterogeneous adipose tissues; and finally, a full heterogeneous model with both heterogeneous adipose and fibroglandular tissues. An 8 mm tumour is placed at different locations within each breast model; a tumour located close to the skin at position (65 mm, 65 mm, 35 mm); at position (88 mm, 65 mm, 45 mm); and at (88 mm, 65 mm, 100 mm).

A Gaussian-based input pulse is transmitted at each of the 50 antennas. The input pulse used in this study is similar to [39] and is different than the pulse described in Chapter 3 in terms of pulse shape, centre frequency and bandwidth. The difference is mainly due to the 3D breast models used in this study, where frequencies above 8 GHz suffer high levels of attenuation in the breast tissues [135].
Therefore, the input pulse used in this study has a centre frequency of 6.0 GHz and a 3-dB bandwidth of 5 GHz similar to [135]. FDTD simulations are conducted at a sampling rate of 576 GHz. Prior to any signal processing, all FDTD signals are down-sampled from 576 to 57.6 GHz.

4.3.2 Performance Metrics

Four metrics are used to evaluate the artifact removal algorithms. The PPRR and Tumour-to-Artifact Ratio (TAR) are applied to the raw radar signals, whereas the SMR and Signal-to-Clutter Ratio (SCR) are calculated from the resultant beamformed images. The PPRR and the SMR are defined in Section 3.3.1. An additional signal metric, TAR, has been defined in order to measure the ability of an algorithm to preserve the tumour response. TAR is defined as the ratio of the tumour peak to the artifact peak.

In addition to the SMR, the SSIM metric was used in Chapter 3 to compare the quality of the images produced using the realistic artifact removal algorithms with the images obtained after ideal artifact removal. However, the image obtained after the subtraction of the skin-only response from the 3D heterogeneous breast phantom (ideal artifact removal) still contains the dominant clutter due to the fibroglandular tissues. Therefore, the comparison of the images obtained after realistic artifact removal with the ideal images is no longer possible. An additional image quality metric, SCR, is defined to measure the quality of beamformed image after the application of a particular artifact removal algorithm. SCR is defined as the ratio of the tumour energy to the strongest clutter energy within the resultant breast image.

4.4 Results

In this section, the results obtained after application of the proposed algorithm to the numerical breast phantoms described in the previous section, are discussed.

The function $D[n]$ is derived from the third-order entropy of backscattered radar signals obtained from the 3D homogeneous breast model, with a tumour located close to the skin at position (65 mm, 65 mm, 35 mm), and the time-window is designed
4. Hybrid Artifact Removal Algorithm

(a) Theoretical dimension and the time-window functions

(b) Original time-window.
Figure 4.2: Theoretical dimension $D[n]$ and time-window functions, (b,c) time-domain signals obtained after multiplying time-window functions and corresponding ideal tumour signals.

by comparing $D[n]$ with a specific threshold. The threshold parameter is set to approximately half of the number of channels (i.e $N_0 = 25$), as suggested by Zhi [37]. Figure 4.2a illustrates the function $D[n]$ and the corresponding artifact-dominant time-window designed using Zhi’s method and using the new maxima-minima approach described in Section 4.2.

The time-window functions obtained from both algorithms are multiplied with the radar signals across all channels in order to remove the artifact. The corresponding artifact-free signals in one channel (channel 24) are shown in Figure 4.2(b,c) (along with ideal tumour signals for comparison). The ideal tumour signals are obtained by subtracting the radar signals recorded from the tumour free homogeneous breast model.

Figure 4.2(b) shows the performance of the existing EBTW algorithm as developed by Zhi, while Figure 4.2(c) shows the effect of the proposed improvement.
in Zhi’s algorithm.

![Image](image1.png)

**Figure 4.3:** Time domain signals after artifact removal, (a) Multiplication with improved time-window (b) Wiener Filter over improved time-window.

![Image](image2.png)

**Figure 4.4:** Time domain signals before (solid lines) and after (dotted lines) artifact removal using proposed hybrid algorithm at 5 different channels: left column is early-time response (artifact) and right column is late-time response (tumour signal) (Note different amplitude ranges between early and late-time signals).
It can be seen from Figure 4.2(b) that the artifact has only been partially removed from the signal, whereas the improved time-window function has mostly removed the artifact as shown in Figure 4.2(c), and the tumour response remains clearly visible.

Figure 4.3(a) shows the effect of the improved Entropy-based Time-Window algorithm as applied to another radar signal, where the artifact and tumour response overlap. It can be seen that, although the artifact has been mostly removed, a significant portion of tumour response signal has also been removed from this particular channel. The solution is to apply the Wiener Filter over the time-window defined by the entropy method, as has been proposed in Section 4.2. This hybrid approach should introduce minimal distortion into the tumour response, as shown in Figure 4.3(b).

It can be seen from Figure 4.3(b) that the artifact has been effectively removed, while the tumour response is preserved. There are some residual artifacts but these have little effect on the beamformed images.

The proposed algorithm is also robust to variation in the early-time artifact as illustrated in Figure 4.4, where the received radar signals before and after artifact removal at five different channels have been plotted. It can be observed that the artifact has been greatly reduced after application of the artifact removal algorithm (dotted line) as compared to the radar signals prior to artifact removal (solid line).
The algorithm is also applied to heterogeneous breast models in order to evaluate the robustness and the effectiveness of the algorithm in the presence of heterogeneity due to fibroglandular tissues.

Figure 4.5 shows the coronal view of the heterogeneous breast model with the tumour located at (88 mm, 65 mm, 100 mm) and the corresponding beamformed image following the application of the proposed hybrid artifact removal algorithm. The beamformed images are obtained using the DAS beamformer [41]. Figure 4.5b shows that the proposed hybrid artifact removal algorithm has successfully reduced the early-stage artifacts, allowing the tumour to be localised in the beamformed image.

Table 4.1 illustrates the performance of the hybrid algorithm (improved Entropy-based Time-Window and Wiener Filter algorithm) in terms of PPRR, TAR, SMR and SCR. The metrics are computed for each individual breast phantom and tumour location used to evaluate the algorithm, and then averaged across all test scenarios. Similar metrics have also been computed for the Zhi’s algorithm and an “ideal” artifact removal method, where the artifact is established using signals obtained from an idealised tumour-free breast model.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>PPRR</th>
<th>TAR</th>
<th>SMR (dB)</th>
<th>SCR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal Subtraction</td>
<td>-104.74</td>
<td>3.24</td>
<td>22.85</td>
<td>2.92</td>
</tr>
<tr>
<td>Zhi’s Algorithm</td>
<td>-41.51</td>
<td>-51.10</td>
<td>-55.42</td>
<td>-113.32</td>
</tr>
<tr>
<td>Proposed Algorithm</td>
<td>-61.30</td>
<td>8.05</td>
<td>18.76</td>
<td>1.60</td>
</tr>
</tbody>
</table>

Examining Table 4.1, the hybrid algorithm has shown an improvement of 20 dB in PPRR and 59 dB in TAR, when compared to the Zhi’s algorithm. The PPRR value of the proposed algorithm is poor when compared to the ideal case as would be expected, but SCR and SMR values are close to the ideal case, which indicates that residual artifacts have little effect on the beamformed images. However, the
EBTW algorithm produced the worst image quality metrics (SCR and SMR), clearly indicating that the artifact removal algorithm had introduced significant distortion into the resultant image.

Overall, the proposed hybrid method provides a good compromise between artifact removal and the tumour response preservation.

4.5 Conclusions

In this chapter, a hybrid artifact removal algorithm for microwave breast imaging applications is presented, which combines the best attributes of two existing algorithms to effectively remove the early-stage artifact while preserving the tumour response.

A time-window is designed based on the entropy values, which represent the artifact-dominant part of the signal. The artifact is then removed by applying the Wiener Filter algorithm over the estimated artifact window.

After artifact removal, beamformed images are obtained using the DAS beamformer. Results indicate that the proposed algorithm provides for an improved artifact-dominant time-window selection. The hybrid approach combining both the improved artifact-dominant window and the Wiener Filter effectively remove the artifact while preserving the tumour response across all channels.

The HAR algorithm is compared to the EBTW algorithm and results indicate that HAR algorithm performs better in terms of signal and image quality metrics, when evaluated using a range of tests from simple homogeneous scenarios to more realistic dielectrically heterogeneous scenarios.

In the following chapter, a multistatic artifact removal algorithm will be presented. The multistatic artifact removal algorithm will extend the proposed hybrid artifact removal algorithm to the more challenging scenario of multistatic radar signals.
5

Multistatic Artifact Removal Algorithm

5.1 Introduction

In the previous chapter, the HAR algorithm was shown to be robust to variation in the artifacts, but it was only applied to monostatic signals obtained from 3D numerical breast phantoms. The variation in monostatic signals is primarily due to the variation in the skin shape and skin thickness. In contrast, multistatic signals exhibit greater variation not only due to the varying skin shape and thickness but also due to the different propagation distances between transmitting and receiving antenna. This variation makes it more challenging to estimate and subsequently remove the artifact when compared to monostatic signals.

Most of the artifact removal algorithms described in Chapter 3 have been solely used with monostatic radar signals, with the exception of the rotation subtraction algorithm [47]. However, the rotation subtraction algorithm is specific to the geometry of the hardware prototype for breast cancer imaging reported in [47].

In this chapter, a novel Multistatic Artifact Removal (MAR) algorithm is proposed. The proposed algorithm extends the HAR algorithm used for monostatic signals to the more challenging scenario of multistatic signals. In the HAR algorithm, the artifact-dominant portion of the signals is estimated using the entropy-based approach, and the artifact is then removed by a Wiener Filter. In the multistatic
artifact removal algorithm, signals containing similar early-stage artifacts are adaptively grouped together based on the entropy method, and each group is separately processed through the HAR algorithm in order to remove the artifacts while preserving the tumour response.

The MAR algorithm facilitates the inclusion of multistatic signals in the imaging process, in addition to the monostatic signals. The combined monostatic and multistatic (CMM) imaging approach improves the imaging quality compared to the monostatic-only imaging approach. The algorithm is evaluated using anatomically and dielectrically accurate 3D numerical breast phantoms and a range of appropriate performance metrics. Results from this work are published in [162], [163].

The remainder of the chapter is organised as follows: Section 5.2 describes the extension of the monostatic HAR algorithm to multistatic artifact removal; Section 5.3 describes the simulation-setup, 3D numerical breast phantoms and the performance metrics; and Section 5.4 details various tests applied to the artifact removal algorithm and corresponding results. Finally, conclusions are drawn in Section 5.5.
5.2 Multistatic Artifact Removal

In this section, the development of the Multistatic Artifact Removal algorithm is described.

The general assumption about the multistatic signal acquisition approach is that an increased number of radar signals provide more information about strong scatterers present within the breast. However, the improvement in the multistatic images may not be incremental as each additional multistatic signal is added [114], [164]. Selection of good quality multistatic signals for multistatic imaging can significantly improve the resultant image, provided that the early-stage artifacts can be effectively removed. The HAR algorithm has shown promising results when applied to monostatic signals due to the similarity of the monostatic artifact in all channels (Figure 5.1(a)). However, it cannot be directly applied to multistatic signals due to greater variation in the artifact (Figure 5.1(b)).

The channel to channel variation in artifact depends upon the propagation path of the signal between the transmitting and the receiving antennas, which makes it more challenging to estimate and remove the artifact. However, it is possible to identify and group multistatic signals having similar artifacts so that the HAR algorithm can be separately applied to each group.

The performance of HAR is dependent on the degree of similarity between the signals in each group, which may vary across all signal groups. This is due to the fact that the Wiener Filter estimates the artifact in a particular channel based on the artifact present in all other channels. If there is greater variation in the artifact in the other channels, the estimated artifact will be less accurate.

Greater variation in the artifacts also affects the artifact-dominant time-window estimation. Therefore, it may not be possible to effectively remove the artifact from each signal group, and it is important to adaptively select only those signal groups where the artifact can be effectively removed for inclusion in the image formation process.
5. Multistatic Artifact Removal Algorithm

5.2.1 Signal Grouping Method

Let $b_{(i,j)}$ be the backscattered signal recorded at antenna $j$, where $i$ is the index of the transmitting antenna, $j$ is the index of the receiving antenna, $i = 1, ..., N$, $j = 1, ..., N$ and $N$ is the total number of antennas in the array.

The signals of the form $b_{(i,i)}$ are monostatic signals with similar early-time artifacts, and therefore can be combined into one group. The early-time artifact is expected to be also similar for signals of the form $b_{(i,i+k)}$ and $b_{(i+k,i)}$ where $i + k \leq N$ and $i$ is the index of the transmitting antenna. Hence, a total number of $L$ groups can be formed \[114\].

The similarity between signals in each group is dependent on the spacing between
the transmitting and receiving antenna pair and also on the distance from the skin. For example, the transmitting-receiving antenna pair \((1, 2)\) and \((6, 7)\) have identical spacing and a common distance from the skin. Therefore the skin-artifact in the signals \(b_{(1,2)}\) and \(b_{(6,7)}\) is similar, as shown in Figure 5.2(b).

It can be seen from Figure 5.2(b) that the degree of similarity between signals of the form \(b_{(i,i+1)}\) is not identical but very similar to the monostatic signals, whereas it decreases with increasing \(k\), as shown in Figure 5.2(c) (where \(k = 2\)) and Figure 5.2(d) (where \(k = 3\)).

The decrease in similarity with increasing \(k\) can be attributed to the increased spacing between the transmitting-receiving antenna pairs and the varying shape of the breast. The decrease in similarity directly affects the performance of the HAR algorithm, which is independently applied to each signal group.

**5.2.2 Adaptive Signal Selection**

An entropy-based method is developed to adaptively select the useful signal groups from a total of \(L\) groups and signals within each group, in order to achieve better SCR in the resultant multistatic images.

In the proposed algorithm, entropy is used to measure the degree of similarity between signals within each group, and compared with other groups in order to select the useful multistatic signals to include in the image reconstruction process. The similarity of the artifacts in the early portion of the radar signals result in a larger value of entropy, whereas much lower entropy values are obtained from the tumour reflections. The \(\alpha - \text{order Renyi entropy}\) was defined for all \(M\) signals in Section 3.2. Equation 3.17 is rewritten for a group of signals as:

\[
H_{\alpha}[n] = \frac{1}{1 - \alpha} \log \left\{ \sum_{i=1}^{Q} (p_i[n])^\alpha \right\} \tag{5.1}
\]

where \(\alpha\) is a real-positive, \(p_i[n]\) is the normalised probability density function created by normalising each radar signal within the group, and \(Q\) is the total number of signals within the group. The entropy changes from \( \log Q \) for similar early-time signals to zero for variations in late-time signals. Third-order entropy is typically
defined for a broad class of signals\textsuperscript{[165]}, therefore $\alpha = 3$ is used in this study. Theoretical dimension of $[b_1[n], b_2[n], \ldots, b_Q[n]]$ is defined as:

$$D[n] = e^{H^*_{\alpha}[n]} \quad (5.2)$$

where $H^*_{\alpha}[n]$ is the smoothed entropy, obtained by applying a smoothing window to Equation (5.1).

$D[n]$ provides the degree of similarity between signals within a group of signals\textsuperscript{[37]}. As expected, the highest degree of similarity is exhibited by the monostatic signals. Therefore, computed $D[n]$ for monostatic signals is used as a benchmark to decide if the degree of similarity between signals in each group is sufficient to effectively remove the artifact from each group.

$D[n]$ for each subsequent signal group is then computed and correlated with the $D[n]$ of the monostatic signals group. Signal groups with a correlation coefficient above a specific threshold are selected with the threshold chosen empirically, whereas the remaining groups are ignored. The signals within each group of the form $b_{(i,i+k)}$ and $b_{(i+k,i)}$ are also chosen on the basis of the correlation coefficient. Any signal negatively affecting the correlation coefficient of that specific group is excluded, and hence only a subgroup of the multistatic signals is selected for use in the image formation process.

Once the signal groups and the signals within each group have been selected, each group is separately processed through the HAR algorithm to remove the artifact. Finally the artifact removed signals are processed through the beamforming algorithm to produce the final breast image.

### 5.3 Simulations and Performance Metrics

In this section, simulations and the development of the numerical breast phantoms are detailed. The performance metrics used for the evaluation of the MAR algorithm are also described.
5. Multistatic Artifact Removal Algorithm

5.3.1 Numerical Breast Phantoms

The 3D numerical breast phantoms used in this study are based on the MRI-derived breast phantoms available from UWCEM breast cancer repository [121]. The breast phantoms are described in detail in Section 3.3.

The FDTD simulation-setup is similar to the setup described in Section 4.3. An antenna array consisting of two rings of Hertzian dipole antennas is positioned around the breast. Each antenna ring contains 25 antenna elements and each antenna is placed at an approximately constant distance from the skin as shown in Figure 5.3. Each antenna transmits a 6.0 GHz differentiated Gaussian pulse with a -3dB bandwidth of 5 GHz and a backscattered waveform is recorded at each of the antenna in the array. The details of the input pulse are described in Section 4.3.

Four breast models with different degree of radiographic density have been considered. A 15 mm tumour model is placed at different locations within each breast model. Table 5.1 describes the radiographic density of each breast model and the corresponding tumour locations.

The performance of the artifact removal algorithm and the imaging process has been evaluated using three performance metrics.

The PPRR is defined in Section 3.3.1. The PPRR is applied to the raw signals and quantifies the artifact removal from a particular channel. The PPRR independently evaluates the performance of the artifact removal algorithm.
Table 5.1: Description of Breast Models

<table>
<thead>
<tr>
<th>Label</th>
<th>Breast Density</th>
<th>Tumour Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>M0</td>
<td>(60 mm, 55 mm, 80 mm)</td>
</tr>
<tr>
<td>2</td>
<td>M1 mostly fat (≤25% glandular tissue)</td>
<td>(55 mm, 60 mm, 65 mm)</td>
</tr>
<tr>
<td></td>
<td>M2</td>
<td>(85 mm, 105 mm, 70 mm)</td>
</tr>
<tr>
<td></td>
<td>M3</td>
<td>(60 mm, 55 mm, 90 mm)</td>
</tr>
<tr>
<td>3</td>
<td>M4 scattered fibroglandular (25-50% glandular)</td>
<td>(45 mm, 50 mm, 105 mm)</td>
</tr>
<tr>
<td></td>
<td>M5</td>
<td>(88 mm, 70 mm, 105 mm)</td>
</tr>
<tr>
<td>4</td>
<td>M6 heterogeneously dense (51-75% glandular)</td>
<td>(60 mm, 110 mm, 70 mm)</td>
</tr>
</tbody>
</table>

The SMR and SCR are computed from the reconstructed breast images. Both the SMR and the SCR are defined in Section 3.3.1 and Section 4.3.1 respectively.

5.4 Results

In this section, the results obtained after the application of the MAR algorithm are discussed.

In order to demonstrate the performance of the multistatic artifact removal algorithm and to compare the imaging results with the monostatic approach, both monostatic and multistatic backscattered signals are first obtained from breast model M0 with tumour located at position (60 mm, 55 mm, 80 mm).

Figure 5.4 shows the third-order entropy based function, \(D[n]\), and the estimated artifact-dominant time-window for each of the signal groups containing all signals of the form \(b_{(i,i+k)}\) where \(k = 0, 1, 2, 3\) and \(k = 0\) is the monostatic group. The artifact-dominant time-window for each group is estimated using the maxima-minima approach [161].

Firstly, the maxima of the function \(D[n]\) is computed and the artifact-dominant time-window is then defined from the start of the signal to the local minima adjacent to the first maxima on the theoretical dimension curve. It can be observed from Figure 5.4(a) that there is a significant difference between the first maxima and the
adjacent minima of $D[n]$ computed from the monostatic signals. However, variation in $D[n]$ increases in the multistatic signals group as $k$ increases (Figure 5.4(b)-5.4(d)).

The increased variation in $D[n]$ is indicative of a corresponding variance in multistatic signals. It becomes difficult to estimate the correct artifact-dominant time-window based on the maxima-minima approach. The difficulty is obvious from a closely located maxima-minima in Figure 5.4(d). In order to obtain artifact free signals, each group of signals is separately processed through the Wiener Filter after the artifact-dominant time-window has been estimated for each group.

Time-domain signals obtained after artifact removal have been plotted in Figure 5.5 (one from each signal group for $k = 0, 1, 2, 3$). The corresponding
ideal tumour signals are also shown for comparison. The ideal tumour signals are produced by the subtraction of the radar signals acquired from with-tumour and tumour-free homogeneous breast models.

It can be observed from Figure 5.5(a)-5.5(c) that the early-stage artifact has been significantly reduced while the tumour response is preserved in the monostatic and multistatic signals of the form $b_{(i+k,i)}$, where $k = 1$. There is still some residual artifact that can be compensated for by incoherent addition at the beamforming stage. However, the residual artifact in the multistatic signals of the form $b_{(i,i+k)}$, where $k = 2$ is slightly greater compared to the monostatic group and the multistatic group with $k = 1$, and it is even poor in the case of multistatic signals of the form...
5. Multistatic Artifact Removal Algorithm

The poor performance of the artifact removal algorithm for signals of the form $b_{(i,i+k)}$ where $k \geq 3$, can be attributed to ambiguity in the artifact-dominant window estimation. Another factor is the poor artifact estimation by the Wiener Filter due to greater variation among signals within this group. Therefore, the group containing signals of the form $b_{(i,i+k)}$ where $k \geq 3$ must be excluded from the image formation process. Inclusion of such groups would contribute negatively towards the SCR in the final image. This information is not known prior to application of the artifact removal. However, it can be predicted based on the entropy-correlation method proposed in Section 5.2.

Figure 5.6(a) shows the correlation coefficient, $r$, computed by the correlation of $D[n]$ of each multistatic signal group (for $k = 1, 2, 3$) with the $D[n]$ of the monostatic signals group. It can be seen that the highest correlation coefficient is obtained from signal groups containing signals of the form $b_{(i,i+k)}$ where $k = 1, 2$ and it significantly drops for $k > 2$. This correlates with the results shown in Figure 5.4.

Hence, the correlation coefficient can be used to limit the number of signal groups that should be included in an image formation process in order to improve the SCR. The CF-DAS algorithm is used to create both the monostatic and the CMM images following the proposed artifact removal algorithm. However, the artifact removal algorithm can be used with any beamformer.

The CMM images are generated by varying the threshold of the correlation coefficient shown in Figure 5.6(a). The image quality metrics (SCR and SMR) are then computed from the resultant images.

The SCR is plotted in Figure 5.6(b) as a function of the total signals used to obtain the CMM images. Different threshold values of the correlation coefficient allow a different number of multistatic radar signals to be included in the image formation process. It can be observed from Figure 5.6(b) that the minimum value of SCR is produced by using only monostatic signals in the imaging process, whereas the SCR is greatly improved by including a number of multistatic signals. A threshold value of 0.91 allows for the inclusion of 48 multistatic signals of the form $b_{(i,i+k)}$, where $k = 3$ (Figure 5.5(d)).
5. Multistatic Artifact Removal Algorithm

Figure 5.6: (a) Correlation coefficient $r$ obtained by correlating $D[n]$ of monostatic signals group with $D[n]$ of multistatic signal groups ($b_{(i,i+k)}$ where $k = 1, 2, 3, 4$), (b) Signal-to-Clutter Ratio (SCR) as a function of the number of signals selected for the imaging process and the value of correlation coefficient $r$ used as threshold for signal selection.

$b_{(i,i+k)}$ and $b_{(i+k,i)}$ where $k = 1$. These additional multistatic signals improve the SCR from approximately 44 dB to 54 dB.

Further relaxing of the threshold value allows even more multistatic signals to be used in the imaging process, which further improves the SCR. Peak SCR is achieved at a threshold value of 0.88, allowing 119 multistatic signals to be used in the image formation process. There is no advantage to using any additional multistatic signals. In fact, these additional signals may reduce the image quality as shown in the Figure 5.6(b) at a threshold value of 0.82. It should also be noted that
5. Multistatic Artifact Removal Algorithm

Figure 5.7: Coronal view of FDTD breast models (a,d,g) showing permittivity of the breast tissues computed at the centre frequency of the pulse, corresponding monostatic beamformed images (b,e,h), and corresponding combined monostatic and multistatic (CMM) images (c,f,i).

A significant improvement in SCR is achieved compared to the monostatic signals, with a threshold value as high as 0.90. Therefore, using a higher value for the threshold would still improve the SCR compared to using monostatic signals alone.

The MAR algorithm is then applied to the heterogeneous breast models in order to evaluate the robustness and effectiveness of the algorithm in the presence of realistic heterogeneity and fibroglandular tissues.

Figures 5.7-5.9 show the coronal view of all FDTD breast models and the corresponding beamformed images following the application of the proposed artifact removal algorithm. The improvement in image quality can be observed by comparing
the monostatic and the CMM beamformed images in each figure.

In particular, the advantage of the CMM imaging is illustrated in images of breast model \( M5 \). The monostatic imaging method fails to localise the tumour due to limited monostatic data, as shown in Figure 5.8(e). However, the tumour can be detected (with a small localisation error) in the CMM image when multistatic
data is also used in addition to the monostatic signals (Figure 5.8(e)).

The localisation error in the images with higher density of fibroglandular tissues can be attributed to the imaging algorithm using an assumed constant propagation speed of microwave signals during the image reconstruction process. Tumour localisation can be improved by estimating the average relative permittivity of the breast using time-of-flight measurements [166], a transmission measurement system [167], or by integrating the 3D permittivity model of the breast as \textit{a-priori} information into the imaging algorithm [147].

Table 5.2 illustrates the performance of CMM imaging in terms of PPRR, SMR and SCR. The images are obtained using the proposed artifact removal algorithm and a GPU-accelerated version of the CF-DAS beamforming algorithm [168]. The metrics are computed for each individual heterogeneous breast phantom, and tumour location used to evaluate the algorithm. Similar metrics have also been computed for monostatic images.

\textbf{Table 5.2:} Performance metrics for the raw signals and the beamformed images

<table>
<thead>
<tr>
<th>Breast Model</th>
<th>Signal Type</th>
<th>Selected Signals</th>
<th>S/C (dB)</th>
<th>S/M (dB)</th>
<th>PPRR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1 Monostatic</td>
<td>25</td>
<td>1.48</td>
<td>23.54</td>
<td>-169.45</td>
<td></td>
</tr>
<tr>
<td>M1 Multistatic</td>
<td>73</td>
<td>3.72</td>
<td>28.62</td>
<td>-152.48</td>
<td></td>
</tr>
<tr>
<td>M2 Monostatic</td>
<td>25</td>
<td>5.63</td>
<td>34.46</td>
<td>-213.98</td>
<td></td>
</tr>
<tr>
<td>M2 Multistatic</td>
<td>109</td>
<td>12.71</td>
<td>48.29</td>
<td>-203.00</td>
<td></td>
</tr>
<tr>
<td>M3 Monostatic</td>
<td>25</td>
<td>5.57</td>
<td>26.52</td>
<td>-172.65</td>
<td></td>
</tr>
<tr>
<td>M3 Multistatic</td>
<td>83</td>
<td>10.02</td>
<td>38.51</td>
<td>-160.13</td>
<td></td>
</tr>
<tr>
<td>M4 Monostatic</td>
<td>40</td>
<td>1.78</td>
<td>21.95</td>
<td>-173.16</td>
<td></td>
</tr>
<tr>
<td>M4 Multistatic</td>
<td>116</td>
<td>6.78</td>
<td>29.50</td>
<td>-154.23</td>
<td></td>
</tr>
<tr>
<td>M5 Monostatic</td>
<td>50</td>
<td>-13.90</td>
<td>14.48</td>
<td>-212.37</td>
<td></td>
</tr>
<tr>
<td>M5 Multistatic</td>
<td>289</td>
<td>2.95</td>
<td>33.90</td>
<td>-198.36</td>
<td></td>
</tr>
<tr>
<td>M6 Monostatic</td>
<td>50</td>
<td>0.87</td>
<td>27.17</td>
<td>-215.63</td>
<td></td>
</tr>
<tr>
<td>M6 Multistatic</td>
<td>278</td>
<td>4.16</td>
<td>37.28</td>
<td>-210.16</td>
<td></td>
</tr>
<tr>
<td>Average Monostatic</td>
<td>3.06</td>
<td>24.69</td>
<td>-192.87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Multistatic</td>
<td>6.74</td>
<td>32.21</td>
<td>-179.73</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Analysing Table 5.2, the multistatic artifact removal followed by the CMM image formation process has shown an average improvement of over 50% in SCR.
and 23% in SMR when compared to monostatic images. However, the PPRR value of the proposed algorithm is slightly poorer than the monostatic HAR algorithm, as would be expected due to the greater variation in early-stage artifacts in multistatic radar signals. The improvements in SCR and SMR values clearly indicate that residual artifacts have a negligible effect on the beamformed images. Overall, the CMM imaging approach supported by the proposed artifact removal algorithm consistently outperforms the monostatic imaging approach.

5.5 Conclusions

In this chapter, a novel adaptive multistatic artifact removal algorithm for microwave breast imaging applications is presented, which extends the monostatic HAR algorithm. Multistatic signals, with similar early-stage artifacts, are grouped together and an entropy-based method is used to adaptively select useful signal groups that will improve the resultant image quality.

The pre-selected multistatic signal groups are then separately processed through the HAR algorithm in order to remove the artifact from the multistatic signals. Finally, the artifact-free signals are used in beamforming to produce improved breast images compared to their monostatic equivalent.

The CMM images obtained after application of multistatic artifact removal are compared with the monostatic images. Results indicate that higher quality multistatic images can be obtained after application of the proposed artifact removal algorithm, calculated across a range of test scenarios, from simple homogeneous to more realistic dielectrically heterogeneous scenarios.

In the following chapter, the HAR algorithm will be applied to the experimental breast phantoms scanned using a prototype system for microwave imaging of the breast.
6

Experimental Evaluation of the Hybrid Artifact Removal Algorithm

6.1 Introduction

In Chapter 4, a novel hybrid artifact removal algorithm for CMI was proposed. The HAR algorithm estimates the artifact-dominant portion of a backscattered radar signal from a given channel based on entropy values. The entropy values are computed from a group of radar signals that are expected to have similar early-time artifacts. The channels located at approximately similar distance from the skin are expected to have highly similar artifacts. Therefore, the HAR algorithm selects these channels for estimation of the artifact-dominant time-window. The Wiener Filter algorithm is then applied to each group to estimate and remove the artifact from each channel within that group. The HAR algorithm was shown to be effective in reducing the early-time artifact, while preserving the tumour response.

The HAR algorithm was evaluated using anatomically and dielectrically accurate 3D numerical breast phantoms, which were simulated using the FDTD method. The antenna array used in simulations consisted of Hertzian dipole antennas. Therefore, the effects of realistic antennas such as gain, directivity and distortions introduced were not considered. In addition, the impact of realistic noise from an experimental system was also not considered. Despite this, the HAR algorithm is expected to be
robust to realistic noise due to its adaptive artifact filtering. In this chapter, the efficacy of the HAR algorithm is evaluated in the presence of realistic antenna effects and noise from an experimental system. The BAVA-D antenna used in the TSAR prototypes developed at the University of Calgary has been used in the evaluation of the HAR algorithm. Some of the other microwave breast imaging prototypes that have been used in patient studies use different antennas. The prototype [134] at the University of Bristol uses UWB wide-slot antenna [133], and a prototype [123] at McGill University uses a resistively loaded dipole named TWTLTA [138]. However, use of a different antenna should not impact the performance of the HAR algorithm due to its adaptive artifact estimation capability.

The robustness of the HAR algorithm to experimental noise is evaluated using both simulated and experimental breast phantoms. The numerical breast phantom and the BAVA-D antenna have been simulated using the FDTD method and experimental breast phantoms have been scanned with the TSAR prototype reported in [60]. The results have been quantified using appropriate performance metrics.

The remainder of the chapter is organised as follows: Section 6.2 describes the development of numerical breast phantom, experimental breast phantoms and scanning process of the experimental breast phantoms; Section 6.3 describes the performance metrics used for the evaluation; Section 6.4 describes the results obtained after application of the HAR algorithm and finally, conclusions are presented in Section 6.5

6.2 Breast Phantoms

In this section, both the numerical breast phantom and the development of the experimental breast phantom are described in detail. In addition, the measurement setup used to collect data from the experimental breast phantoms and the preprocessing of the measurement data are also described.
6. Experimental Evaluation of the Hybrid Artifact Removal Algorithm

Figure 6.1: An example of an internal structure configuration attached to a polycarbonate disk (right) to be placed inside a skin layer (left). Two possible tumours attached to polycarbonate rods are shown below (© 2015 IEEE. Reprinted, from [146]).

6.2.1 Numerical Breast Phantom

A numerical breast model with a geometry similar to that of the experimental breast phantom is created. A 16 mm diameter tumour is placed at (-25 mm, 0 mm, -17.3 mm). The skin layer and the interior of the model are assigned the same dielectric properties that are used to develop the experimental breast phantoms. A UWB antenna is scanned around the breast to transmit and collect the reflection data [144].

The antenna is excited with a differentiated Gaussian pulse [144] of centre frequency 4 GHz and an approximate bandwidth of 5 GHz. Reflection data is recorded at 20 azimuth locations around the breast. For each azimuth location, the antenna is moved vertically along the breast and reflections are recorded at 7 equally spaced vertical positions, producing 140 signals. The scan locations and the scan pattern are similar to the ones used to scan the experimental breast phantom.

The BAVA-D antenna [144] is used to illuminate the breast and record the corresponding reflections. The breast model is simulated using a FDTD solver. The dielectric properties of breast tissues and immersion liquid are incorporated using Debye model.
6.2.2 Experimental Breast Phantoms

6.2.2.1 Breast Phantom Development

The experimental breast phantoms used in this study have been described in [146]. The breast phantoms include materials representing skin tissue, fatty tissue, glandular tissue and tumour tissue. A skin layer with 2 mm thickness, 10 cm diameter and 9 cm depth (from chest wall to nipple) [169] is created using a skin mould. The skin mould is created with a 3D printer (Replicator 2, MakerBot Industries, Brooklyn, NY) and then filled with a carbon/rubber mixture to create the skin layer.

The internal structures, such as tumour and glandular structures, are also created with a 3D printer and a carbon/urethane rubber mixture is used to create the tumour and glandular tissue mimicking material. The carbon concentration in the carbon/urethane rubber mixture is varied to mimic the dielectric properties of glandular structures and tumour tissue. The specific concentrations of carbon/rubber mixture for skin, glandular, tumour and fatty tissues are given in Table 6.1. The dielectric properties of each breast phantom material (BPM) are shown in Figure 6.2.

The tumour and glandular structures are glued to nylon threaded rods and bolted to a polycarbonate disk. The polycarbonate disk is then placed inside the skin layer. Figure 6.1 shows the skin layer, the glandular structures attached to the polycarbonate disk and the tumours. The skin layer is then filled with canola oil to mimic fatty tissue.

Two experimental breast phantoms have been used in this study. The first breast phantom has a skin layer, fatty tissue and a 16 mm diameter tumour located at (7 mm, 13 mm, -50.5 mm). The second breast phantom contains a skin layer,

Table 6.1: Chosen Carbon-based mixtures for various soft tissues found in the breast (© 2015 IEEE. Reprinted, from [146]).

<table>
<thead>
<tr>
<th>Tissue Type</th>
<th>Graphite (wt%)</th>
<th>Carbon Black (wt%)</th>
<th>Urethane (wt%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fatty</td>
<td>10-20</td>
<td>0</td>
<td>80-90</td>
</tr>
<tr>
<td>Skin</td>
<td>30</td>
<td>4</td>
<td>66</td>
</tr>
<tr>
<td>Glandular</td>
<td>30</td>
<td>7</td>
<td>63</td>
</tr>
<tr>
<td>Tumour</td>
<td>30</td>
<td>≥ 7</td>
<td>≤ 63</td>
</tr>
</tbody>
</table>
Figure 6.2: Dielectric properties of breast phantom material (BPM) used in development of experimental breast phantoms. The dry skin \cite{120}, high-property glandular, low-property glandular and fatty tissue \cite{84} dielectric properties included for comparison (© 2015 IEEE. Reprinted, from \cite{146}).

a 40 mm diameter cylindrical glandular structure, which extends from the tip of the breast to the polycarbonate lid as shown in the Figure 6.3 and a 16 mm tumour located at (-28 mm, 12 mm, -31 mm).

6.2.2.2 Data Acquisition

The measurement data is collected using the prototype system described in \cite{60}. In order to collect the measurement data, the breast phantoms are placed in a tank filled with canola oil as shown in Figure 6.4. The oil acts as an immersion/coupling liquid. The prototype system has a single BAVA-D \cite{144} antenna that can be positioned around the breast at various azimuth and elevation angles.

The second generation TSAR prototype has two additional degrees of freedom to control the proximity and orientation of the antenna relative to the breast skin. For each breast phantom, the antenna is positioned at 7 elevations along the breast
height. For each elevation, measurements are collected at 20 equally spaced positions around the breast. The antenna is positioned 10 mm from the skin and is oriented perpendicular to the skin for each measurement.

A vector network analyser (PNA-X N5242A or PNA-L N5232A, Agilent Technologies, Santa Clara, CA) is used to collect the measurement data. Measurements are acquired at 1200 frequencies between 10 MHz and 12 GHz with, a 1 kHz Intermediate Frequency (IF) bandwidth. The average of 3 measurements is computed [146]. The frequency-domain data is then pre-processed before imaging and will be described in the following section.
6. Experimental Evaluation of the Hybrid Artifact Removal Algorithm

6.2.2.3 Pre-processing

The frequency-domain data is calibrated prior to the application of the artifact removal algorithms and final imaging. The calibration is performed by subtracting measurements that were collected at the same antenna positions but in the absence of the breast phantom.

A phase-shift is also introduced in the calibrated data to compensate for the antenna aperture location. The calibrated frequency-domain data is then weighted with a differentiated Gaussian pulse of centre frequency 4 GHz and an approximate bandwidth of 5 GHz. Finally, an inverse Chirp-Z transform \(^{36}\) is used to convert the frequency-domain data to the time-domain for processing through the artifact removal and imaging algorithms.

6.3 Performance Metrics

In this section, the metrics used for the experimental evaluation of the HAR algorithm are described.

6.3.1 Peak-to-Peak Response Ratio

The PPRR is defined in Section 3.3.1. It is computed for each radar signal measured from the breast phantom and it measures the efficacy of an artifact removal algorithm to suppress the early-time artifacts.

6.3.2 Signal-to-Clutter Ratio

The SCR is used to estimate image quality. The SCR was defined in Chapter 4 as the ratio of the tumour intensity to clutter intensity within an image. In the previous chapters, the tumour intensity was computed from the known tumour size. In this chapter, the Full-width Half Maximum (FWHM) is introduced to automatically estimate the extent of the tumour and clutter regions for the SCR computation.

The overall 3D image is divided into connected regions of different intensity levels present in the image. The highest intensity level region is considered to be the tumour region and the region with the second highest intensity level is
considered to be clutter. The extent of both regions is defined by computing the FWHM. The FWHM is computed by growing a region around the centroid until the intensity of the region drops by half. The average Euclidean distance from the centroid of the tumour to the end of the region is estimated to be the FWHM. The SCR is then computed as the ratio of the average intensity in the tumour region to the average intensity of the clutter.

6.3.3 Signal-to-Mean Ratio

The SMR is another metric of the quality of the beamformed image that provides a measure of the separation between the tumour intensity and the background clutter. It was defined in Chapter 4 as the ratio of the average intensity of the tumour region to the average intensity of the overall image. The tumour region used in the computation of the SMR is also estimated by the computation of the FWHM as described above.

6.4 Results

In this section, the time-domain signals obtained after application of the HAR algorithm and the corresponding imaging results are shown and discussed.

The signals recorded at the antennas located at the same elevation angle are grouped together. The measurements are collected at 20 azimuth locations for each elevation angle. There are a total of 7 elevation angles and therefore the signals are arranged in 7 groups, with each group having 20 signals.

The HAR algorithm is applied to each group independently. The artifact-dominant time-window is estimated for each group of signals. The Wiener Filter is then optimised over the artifact-dominant time-window to estimate the artifact at each channel from the artifact at all other channels within the group. The estimated artifact is subtracted from each channel to obtain the artifact-free signal.

Firstly, the numerical model is processed through the HAR algorithm and a subset of artifact-free signals is plotted in Figure 6.6. The corresponding ideal tumour response at each channel is also plotted for comparison. The ideal tumour
response is obtained by subtracting the signals collected from the tumour-bearing breast model from the signals of the tumour-free breast model.

Figure 6.5: The backscattered time-domain signal recorded at Channel 8; the corresponding ideal tumour response; and the corresponding Hybrid Artifact Removal (HAR) processed signal.

Figure 6.5 shows a backscattered time-domain signal received at channel 8, along with the corresponding ideal tumour response and the corresponding HAR processed signal. The early-time part of the backscattered signal is essentially the early-time artifact and the late-time part of the signal is the response from the interior of the breast.

It can be seen from Figure 6.5 that the late-time part of the backscattered signal has significantly higher energy than the ideal tumour response. This higher energy can be attributed to late-time clutter due to healthy breast tissues, as well as realistic antenna effects. The late-time clutter, along with the early-time artifact, may impede the detection of the tumour. Therefore, both type of artifacts must be removed prior to imaging, while preserving the tumour response.

Figure 6.5 shows that the HAR algorithm has not only removed the early-time artifact but the late-time clutter has also been significantly reduced. The resultant signal is very similar to the ideal tumour response. Figure 6.6 shows the comparison
of the ideal tumour response and the corresponding HAR processed signals at the selected channels. In most cases, the artifact has been significantly suppressed by the HAR algorithm and the tumour response has been preserved. Tumour response preservation can be observed from the similarity between the ideal tumour responses and the HAR processed signals. However, in some cases there is a residual artifact, as shown in Figure 6.6(d). This artifact can potentially be compensated for by incoherent addition at the imaging stage.

The efficacy of the HAR algorithm in suppressing the early-time artifacts is quantified by computing the PPRR for each signal of the breast phantom. Table 6.2 shows the mean PPRR for both the numerical and experimental breast phantoms.
The average PPRR across all breast phantoms is -126.28 dB, which indicates a significant reduction in the early-time artifacts for the both the numerical and the experimental breast phantoms. The HAR processed signals of both the numerical and the experimental breast phantoms are then imaged using the DAS algorithm. Figure 6.7 shows the image of the numerical breast phantom where three 2D slices of the 3D volumetric image are shown. The tumour is accurately localised in all three slices, with almost no clutter, and the tumour intensity is significantly higher than the background.

Figure 6.8 shows the images of the experimental phantoms. The tumour can be correctly localised in both images. However, clutter can also be observed in these images. This clutter can be attributed to the late-time clutter in the radar signals due to fatty tissues, glandular tissues, and antenna effects as described earlier.

Figure 6.8b shows the image of the experimental phantom. The only significant intensity region in the image corresponds to the tumour location. The gland response
Figure 6.8: Beamformed images of the experimental phantoms after artifact removal using the Hybrid Artifact Removal (HAR) algorithm, (a) with tumour, (b) with tumour and gland.
does not appear in the image. This is due to the fact that the HAR algorithm has not only removed the early-time artifacts, but it has also removed the clutter due to the glandular insert. The gland response appears similar at most of antennas due to its shape and the location. Therefore, the HAR algorithm is able to remove the response from this glandular insert.

Table 6.2 summarises the imaging performance metrics. The SCR and SMR values for the numerical breast model are higher than the SCR and SMR values for the experimental phantoms, as is expected. The experimental phantom with the tumour inclusion has higher SCR and SMR values compared to the experimental phantom with the tumour and the glandular inclusion. Again, this is an expected result since the gland has higher permittivity than the background media; it is expected to reflect a significant amount of energy, in a similar way, to the tumour. Therefore, it is expected to result in higher clutter in the final image.

<table>
<thead>
<tr>
<th>Breast Phantoms</th>
<th>PPRR (dB)</th>
<th>SCR (dB)</th>
<th>SMR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Numerical Phantom</td>
<td>-132.81</td>
<td>20.08</td>
<td>52.15</td>
</tr>
<tr>
<td>Experimental Phantom with Tumour</td>
<td>-125.53</td>
<td>11.28</td>
<td>31.89</td>
</tr>
<tr>
<td>Experimental Phantom with Tumour and Gland</td>
<td>-120.49</td>
<td>6.84</td>
<td>29.57</td>
</tr>
</tbody>
</table>

In summary, the HAR algorithm has significantly reduced the early-time artifact for both the simulated and the experimental breast phantoms, as indicated by the signals and the PPRR metric. The images produced after application of the HAR algorithm and the corresponding imaging performance metrics also showcase the good artifact suppression capability of the HAR algorithm, while preserving the tumour response.
6.5 Conclusions

In this chapter, the artifact suppression capability of the HAR algorithm is evaluated using data from a numerical model and experimental prototype.

A numerical breast model is simulated with a BAVA-D antenna using the FDTD solver. The experimental breast phantoms and the interior tissue structures are developed using 3D printed moulds. Different concentrations of carbon/urethane rubber mixture are used to mimic the dielectric properties of breast skin, tumour tissue and glandular tissue. The experimental breast phantoms are scanned with the TSAR prototype, which uses a single BAVA-D antenna to scan the breast.

The HAR algorithm is applied to the signals collected from both the numerical and experimental breast phantoms. The efficacy of the HAR algorithm to suppress the early-time artifacts is demonstrated by computing the PPRR metric. The HAR processed signals are then used to produce the final images. The results indicate that the HAR algorithm not only suppressed the early-time artifact but also reduced the clutter due to the realistic antenna and the experimental system, while preserving the tumour response.

In the following chapter, the HAR algorithm will be evaluated for various scan configurations used by different prototypes developed for microwave breast imaging.
7

Artifact Removal for Various Scan Configurations

7.1 Introduction

Several prototypes for microwave imaging of the breast have been developed by various research groups [60], [61], [123], [134], [170], [171]. Each prototype uses a different antenna type and different antenna positioning systems for scanning the breast. For example, the TSAR prototype reported in [61] uses a cylindrical scan configuration. The prototype reported in [134] uses a hemispherical scan configuration, and a patient-specific scan configuration is used in the second generation TSAR prototype [60].

The choice of different antenna for different prototypes may not impact the performance of the HAR algorithm due to its adaptive artifact estimation capability, as demonstrated in the previous chapter. However, the performance may vary with a different scan configuration. Each scan configuration positions antennas at different distances from the breast, resulting in additional variation in the early-time artifacts. These additional variations may impact the performance of the artifact removal algorithm.

The research group at the University of Calgary has developed an early-time artifact removal algorithm, namely Neighbourhood-based Skin Subtraction...
The NSS algorithm improves upon the filter-based method proposed in \cite{35}. The NSS algorithm introduces a method to select a cluster of neighbouring channels around the target channel, in order to estimate the artifact in the target channel. Appropriate selection of the neighbourhood improves the artifact estimation by using signals that are similar to the target signal. The NSS algorithm also introduces an automatic method to select the artifact-dominant portion of the signal for filter weight computation. The improvement in results has been demonstrated by applying the NSS algorithm to 3D numerical, simple experimental breast phantoms, and to patient data \cite{172}.

Both the NSS and the HAR algorithm overcome the limitations of the filter-based algorithm \cite{35} by proposing methods which estimate the artifact-dominant time-window and also select appropriate neighbouring antennas for artifact estimation. Both algorithms have shown promising results in 3D scenarios. However, these algorithms have only been evaluated separately, on different breast phantoms and different scan configurations.

In this chapter, the efficacy of both algorithms has been evaluated using common numerical as well as experimental breast phantoms, scanned with different scan patterns. These scan patterns include the following:

- cylindrical,
- hemispherical,
- adaptive/patient-specific.

The cylindrical scan pattern is the same as that used in the TSAR prototype \cite{61}, which has also been used in a patient study \cite{169}. A number of other prototypes that use the cylindrical scan pattern are reported in \cite{170}, \cite{171}. The hemispherical scan pattern is similar to the pattern used in the prototype system evaluated in clinical trials reported in \cite{134}. Another example of a prototype system that houses antennas in a hemispherical radome is described in \cite{123}. The patient-specific scan pattern is used in the second generation TSAR prototype \cite{60}. These different scan
patterns facilitate the evaluation of the robustness of artifact removal algorithms against various existing scan configurations.

The various scan configurations considered in this study also allow the generalisability of the results presented here across a large number of monostatic breast imaging prototype systems. Even though different prototypes use different hardware and in particular different antenna types, both algorithms can still be applied to the acquired data. This is due to the fact that the performance of both algorithms is affected by the placement of the antenna (scan pattern) and not by the antenna type used for the measurements.

Two numerical breast phantoms have been constructed from laser data acquired during a patient study at the University of Calgary [169]. The realistic breast shape presents a challenging scenario for the artifact removal algorithms. A third numerical breast phantom has been derived from an MRI of a real patient and therefore is also representative of a realistic breast. Experimental breast phantoms have also been used to evaluate the performance of both algorithms in the presence of realistic noise. These experimental breast phantoms are created with dielectric properties close to those of human tissues for both skin and internal structures of the breast. The results have been compared using a range of appropriate signal and image quality metrics. Preliminary results from this work were presented in [173], and detailed results are published in [174].

The remainder of the chapter is organised as follows: Section 7.2 describes the artifact removal algorithms; Section 7.3 describes the imaging algorithm used in this study, the various simulated breast phantoms, and the experimental breast phantoms; the pre-processing steps applied to the data before imaging are covered in Section 7.4; Section 7.5 describes the performance metrics used to evaluate the algorithms; Section 7.6 presents the results and discussion; and finally the conclusions and suggestions for future work are discussed in Section 7.7.
7.2 Artifact Removal Algorithms

In this section, the NSS algorithm is described. The HAR algorithm has been detailed in Chapter 4.

7.2.1 Neighbourhood-based Skin Subtraction Algorithm

The NSS algorithm estimates the artifact in a particular channel from the neighbourhood channels that are expected to contain similar early-stage artifacts. The artifact is estimated using a filter-based method described in, where the filter weights are optimised over the artifact-dominant time-window. The NSS algorithm uses only neighbouring channels for the estimation of the artifact, unlike all channels used in. Furthermore, an automatic method to select the artifact-dominant window is used to optimise the filter weights. The following subsections briefly describe the time-window selection and neighbourhood selection algorithms.

7.2.1.1 Artifact-Dominant Window Selection

The NSS algorithm first processes backscattered radar signals, collected at each channel, through an artifact-dominant window selection algorithm. The undesired early-time artifact tends to be several orders of magnitude larger than responses from internal structures. The algorithm assumes that the early-time artifact can be isolated by finding the maxima greater than a predetermined threshold value. The start of the artifact-dominant window is set equal to the time step corresponding to the trough that precedes the first significant peak. The end of the artifact-dominant window is defined as the time step corresponding to the trough that follows the last significant peak. The artifact-dominant time-window computed for a sample signal is shown in Figure 7.1.

7.2.1.2 Neighbourhood Selection

The neighbouring antennas of a target antenna are defined based on: the spacing between the target antenna and the neighbouring antennas, and the cross-correlation
7. Artifact Removal for Various Scan Configurations

between the signal recorded at the target antenna and the neighbouring antennas [172]. The reflections from each neighbouring antenna are then cross-correlated with the reflection from the target antenna to validate the similarity of reflections. Next, a pre-calculated threshold is used to validate the similarity of reflections from antennas included in the neighbourhood of the target antenna. The signals from any antenna not meeting the similarity criteria are excluded from the neighbourhood. The similarity criteria ensures that signals selected in the neighbourhood have enough similarity to provide an accurate estimate of the artifact in the target antenna.

7.2.1.3 Artifact Filtering

The artifact filtering process is similar to the one described in Section 3.2.3. Equation 3.3 is used to remove the artifacts from each antenna $i$ and is rewritten as:

$$ s_\tau[n] = b_\tau[n] - q^T b_{\text{neighbours},i}[n] \quad (7.1) $$

where $\tau$ is the target antenna, $b_{\text{neighbours},\tau}[n]$ is the combination of signals from neighbourhood antennas selected for the target antenna $i$, and $q$ are the filter
weights. The filter weights are calculated as:

\[ q = \arg \min_q \sum_{n=w_1}^{w_2} \left| b_i[n] - q^T b_{\text{neighbours},i}[n] \right|^2 \tag{7.2} \]

where \( w_1 \) and \( w_2 \) are the start and end respectively of the artifact-dominant window calculated, as explained in the previous subsection. Eq. 7.2 can be solved as described in [172].

7.3 Imaging

A [DAS] imaging algorithm [169] is used to form the final breast images. The traditional [DAS] algorithm has been used in this study because [DAS] does not employ any additional clutter suppression techniques, and therefore the performance of the artifact removal algorithm can be evaluated in isolation. The artifact-free backscattered radar signals are time-aligned, summed and then squared for each synthetic focal point \( \vec{r} = (x, y, z) \) within the breast. The 3D energy profile of the breast is created as follows:

\[ I(\vec{r}) = \left( \sum_{i=1}^{M} b_i(\tau_i(\vec{r})) \right)^2 \tag{7.3} \]

where \( M \) is the total number of channels, \( b_i \) is the backscattered signal recorded at channel \( i \), \( \tau_i(\vec{r}) \) is the time required to travel the round trip distance between focal point \( \vec{r} \) and the antenna \( i \).

\( \tau_i(\vec{r}) \) is dependent on the propagation speed of the electromagnetic wave. An average propagation speed is typically used to estimate \( \tau_i(\vec{r}) \). The imaging algorithms in previous chapters used an average propagation speed based on an assumed averaged permittivity of the breast. However, the propagation speed varies as the wave travels through the immersion medium, breast skin and the interior of the breast due to different permittivity values. Therefore, a separate propagation speed is computed based on the estimated permittivity of each medium. A separate propagation speed corresponding to the distance travelled in each medium allows for a more accurate estimation of \( \tau_i(\vec{r}) \).
The distance travelled by the interrogating signal in the immersion medium, skin and the interior of the breast is estimated from the outline of the breast surface. The breast surface is estimated from the laser data collected during the scanning of the experimental breast phantoms [175]. The TSAR prototype at the University of Calgary is equipped with a sophisticated laser system that allows for the estimation of the breast surface from laser data collected during the breast scan. The laser system and the TSAR prototype is detailed in Section 6.2.2.

7.4 Breast Phantoms

In this section, the numerical breast phantoms are described. The same experimental breast phantoms as described in Section 6.2.2 are used again in this study.

7.4.1 Numerical Breast Phantoms

![Figure 7.2: Large breast phantom and scan patterns, (a) Cylindrical, (b) Hemispherical, (c) Patient-specific, (d) Orientation of antenna corresponding to fourth position of hemispherical scan pattern (© 2015 IEEE. Reprinted, from [176])](image)

Three numerical breast phantoms have been considered in this study. The laser data acquired in the patient study [169] (study E-22121 approved by the Conjoint Health Research Ethics Board, University of Calgary) has been used to
reconstruct realistic skin surfaces for the first two breast phantoms. The mean skin thickness is 2 mm and the internal breast tissues have been modelled as homogeneous fat. A 15 mm diameter tumour is included in each breast phantom at different locations, as described in Table 7.1.

The internal tissue structure of the first two breasts is modelled as homogeneous fat, as opposed to more realistic heterogeneous tissue structures. This simplification allows us to solely evaluate the performance of the early-stage artifact removal algorithms. The primary source of early-stage artifacts is the skin response. However, the quantification of clutter due to early-stage artifacts in the images becomes ambiguous in the presence of heterogeneous breast tissues. In the absence of heterogeneous tissues, clutter in the images can be attributed to the residual artifacts.

The challenge for artifact removal algorithms is variations in skin shape, curvature and thickness. Tumours located close to the skin also present a challenge, as the tumour response may be embedded in the skin response and could be distorted by the artifact removal algorithm. Another issue is the various scan configurations. The breast phantoms used in this study have been designed taking these challenges into consideration. The third numerical breast phantom is derived from a MR

Figure 7.3: Small breast phantom and scan patterns, (a) Cylindrical, (b) Hemispherical, (c) Patient-specific (© 2015 IEEE. Reprinted, from [176])
Figure 7.4: Heterogeneous breast phantom derived from a Magnetic Resonance Imaging (MRI) scan of a patient showing distribution of different breast tissues with (a) and (b) showing side view, (c) showing top view and (d) showing bottom view. Three different types of glandular tissues are shown in different colours (© 2015 IEEE. Reprinted, from [176]).

scan of a patient, and the interior is composed of fat as well as three different types of glandular tissue as shown in Figure 7.4.

These numerical breast phantoms are modelled as immersed in canola oil. A UWB antenna is modelled and scanned around the breast to transmit and collect the reflection data [144]. All numerical breast phantoms are scanned with three different scan patterns: a cylindrical scan pattern; a hemispherical scan pattern; and a patient-specific scan pattern. The scan patterns are shown in Figure 7.2-7.3 and described in detail in [176].

The antenna is excited with a differentiated Gaussian pulse of centre frequency 4 GHz and FWHM between 1.3 to 7.6 GHz [146]. Reflection data is recorded at 30 azimuth locations around the breast. For each azimuth location, the antenna
Table 7.1: Summary of numerical and experimental breast phantoms used in this study

<table>
<thead>
<tr>
<th>Phantom Label</th>
<th>Phantom Type</th>
<th>Scan Configuration</th>
<th>Tumour Location</th>
<th>Tumour Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>Homogeneous Small</td>
<td>Cylindrical</td>
<td>(-15, 0, -12)</td>
<td>15mm</td>
</tr>
<tr>
<td>C2</td>
<td>Homogeneous Large</td>
<td>Cylindrical</td>
<td>(24, 3, -17)</td>
<td>15mm</td>
</tr>
<tr>
<td>C3</td>
<td>MRI-based Heterogeneous</td>
<td>Cylindrical</td>
<td>(-27, 11, -27)</td>
<td>15mm</td>
</tr>
<tr>
<td>H1</td>
<td>Homogeneous Small</td>
<td>Hemispherical</td>
<td>(-15, 0, -12)</td>
<td>15mm</td>
</tr>
<tr>
<td>H2</td>
<td>Homogeneous Large</td>
<td>Hemispherical</td>
<td>(24, 3, -17)</td>
<td>15mm</td>
</tr>
<tr>
<td>H3</td>
<td>MRI-based Heterogeneous</td>
<td>Hemispherical</td>
<td>(-27, 11, -27)</td>
<td>15mm</td>
</tr>
<tr>
<td>P1</td>
<td>Homogeneous Large</td>
<td>Patient Specific</td>
<td>(24, 3, -17)</td>
<td>15mm</td>
</tr>
<tr>
<td>P2</td>
<td>Homogeneous Small</td>
<td>Patient Specific</td>
<td>(-15, 0, -12)</td>
<td>15mm</td>
</tr>
<tr>
<td>P3</td>
<td>MRI-based Heterogeneous</td>
<td>Patient Specific</td>
<td>(-27, 11, -27)</td>
<td>15mm</td>
</tr>
<tr>
<td>P4</td>
<td>Simulation of E1</td>
<td>Patient Specific</td>
<td>(25, 0, -17.3)</td>
<td>16mm</td>
</tr>
<tr>
<td>E1</td>
<td>Experimental</td>
<td>Patient Specific</td>
<td>(7, 13, -50.5)</td>
<td>16mm</td>
</tr>
<tr>
<td>E2</td>
<td>Experimental with glandular inclusion</td>
<td>Patient Specific</td>
<td>(-28, 12, -31)</td>
<td>16mm</td>
</tr>
</tbody>
</table>

is moved vertically along the breast and reflections are recorded at 10 equally spaced vertical positions, producing 300 signals. The BAVA-D [144] antenna is used to illuminate the breast and record the corresponding reflections. The breast models are simulated using a FDTD solver. The dielectric properties of breast tissues and the immersion liquid are incorporated using Debye models. The Debye parameters are detailed in Table. 7.2.

7.5 Performance Metrics

In this section the performance metrics are described. The signal analysis metrics are chosen to evaluate the ability of each algorithm to suppress the early-time skin artifacts and quantify the impact of the artifact removal algorithm on the late-time clutter and tumour reflections. The image quality metrics have been chosen to
measures the quality of images in terms of accuracy of tumour localisation, extent of tumour response and intensity of tumour response.

### 7.5.1 Signal Analysis Metrics

#### 7.5.1.1 Artifact Suppression Ratio

The Artifact Suppression Ratio (ASR) measures the efficacy of the artifact removal algorithm to suppress the early-stage artifact. The ASR is defined as the ratio of the energy of the artifact, following and prior to the application of an artifact removal algorithm. The ASR quantifies the energy of residual artifacts after the artifact removal process, which may contribute to the clutter in the images. A high value of ASR indicates larger residual artifacts, whereas a lower ASR value indicates that the residual artifacts are minimal. The ASR is given as

\[
ASR = 10 \log \left( \frac{\sum_{n_o}^{m_o} |s[n]|^2}{\sum_{n_o}^{m_o} |b[n]|^2} \right)
\]  

(7.4)

where \(b[n]\) is the backscattered signal prior to artifact removal, \(s[n]\) is the signal following artifact removal, and \(n_o\) and \(m_o\) are the start and end of the artifact-dominant time-window respectively.
7.5.1.2 Tumour and Clutter Suppression Ratio

The Tumour and Clutter Suppression Ratio (TCSR) measures the impact of the artifact removal process on the energy of the late-time signal that contains the tumour response and clutter.

TCSR is the ratio of energy of the signal outside the artifact-dominant time-window following, and prior to, the application of artifact removal. A high value of TCSR indicates a minimal effect on the late-time signal, whereas a lower value indicates better late-time clutter suppression. TCSR is given as

$$TCSR = 10 \log \left( \frac{\sum_{m_o+1}^N |s[n]|^2}{\sum_{m_o+1}^N |b[n]|^2} \right) \quad (7.5)$$

where $m_o$ is the end of the artifact-dominant time-window and $N$ is the total length of the time-domain signal.

The late-time clutter is primarily related to the reflections from healthy breast tissues and is often reduced by the artifact removal process. However, the late-time signal also contains the tumour response that can also be affected by late-time clutter suppression. The effect on the actual tumour response is measured with another signal metric described in the following subsection.

7.5.1.3 Tumour Energy Preservation Ratio

The Tumour Energy Preservation Ratio (TEPR) measures the ability of an artifact removal algorithm to preserve the tumour response while removing the artifact.

The TEPR is defined as the ratio of tumour energy obtained from the isolated tumour response ($t_{isolated}[n]$) to the ideal tumour response ($t_{ideal}[n]$). The TEPR is given as

$$TEPR = 10 \log \left( \frac{\sum_{t_1}^{t_2} |t_{isolated}[n]|^2}{\sum_{t_1}^{t_2} |t_{ideal}[n]|^2} \right) \quad (7.6)$$

where, $t_1$ and $t_2$ are the start and end of the time-window containing the ideal tumour response.
7. Artifact Removal for Various Scan Configurations

The tumour response in the artifact removed signals is isolated from late-time clutter by subtracting the artifact removed signals from tumour-bearing and tumour-free phantoms. The ideal tumour response is obtained by subtracting the backscattered signals received from tumour-bearing and tumour-free breast phantoms.

Ideally, the artifact removal algorithm should not change the tumour response and TEPR should be close to 0 dB. However, in practice, the tumour response is almost always affected and the TEPR quantifies the change introduced in the tumour response by an artifact removal algorithm.

7.5.2 Image Quality Metrics

7.5.2.1 Full-Width at Half Maximum

The FWHM is used to estimate the extent of the tumour response in the image. The FWHM is defined as the distance from the peak tumour intensity to the point where the tumour intensity drops by half and is detailed in Section 6.3.2.

7.5.2.2 Signal-to-Clutter Ratio

The SCR is used to estimate the image quality. The SCR is defined as the ratio of tumour intensity to clutter intensity in the 3D image. The SCR is calculated from the beamformed image obtained following artifact removal and is detailed in Section 6.3.2.

7.5.2.3 Signal-to-Mean Ratio

The SMR is another measure of the quality of the beamformed image. It is defined as the ratio of the average intensity of the tumour region to the average intensity of the overall 3D image and is detailed in Section 6.3.3.

7.6 Results

In this section, the results obtained after application of the artifact removal algorithms to both the numerical and the experimental breast phantoms are discussed. Firstly, the artifact-removed signals obtained from each artifact removal
algorithm are analysed and compared using the signal metrics. Next, the images are generated from the same artifact-removed signals and image quality is assessed and compared using the image quality metrics.

7.6.1 Signal Analysis

7.6.1.1 Artifact Suppression Ratio

![Figure 7.5](image)

**Figure 7.5:** The mean Artifact Suppression Ratio (ASR) of each breast phantom is shown. The ASR is computed for each radar signal (after processing through both HAR NSS) and averaged across each breast phantom. Lower value indicates better artifact suppression.

The ASR measures the ability of the artifact removal algorithm to reduce artifacts. The backscattered radar signals from each breast phantom described in Table 7.1 are processed through both the NSS and HAR algorithms to remove the early-time artifacts. The ASR is computed for each radar signal and averaged across each breast phantom. Figure 7.5 shows the average ASR computed from each breast phantom for each artifact removal algorithm.

The NSS algorithm demonstrates better artifact suppression capability for all phantoms, including the MRI-based heterogeneous phantom, with significantly lower ASR values compared to the HAR algorithm. However, the average ASR
Figure 7.6: The mean Tumour and Clutter Suppression Ratio (TCSR) of each breast phantom is shown. The TCSR is computed for each radar signal (after processing through both HAR and NSS) averaged across each breast phantom. Lower values indicate better clutter suppression but also greater tumour suppression.

Values of the HAR algorithm also remain significantly below 0 dB indicating a significant reduction in the artifacts.

Better artifact suppression by the NSS algorithm may largely be attributed to the neighbourhood selection method, where only signals with highly similar artifacts are used to estimate the artifact in a particular channel.

7.6.1.2 Tumour and Clutter Suppression Ratio

The TCSR metric evaluates the impact of artifact removal on the late-time signal containing the tumour response as well as clutter due to healthy breast tissues. Figure 7.6 shows the average TCSR of each breast phantom computed for both NSS and HAR algorithms.

The low values of TCSR for the NSS algorithm indicate that the NSS not only effectively suppresses the artifact but also reduces the late-time response containing the tumour and clutter. In particular, a significant reduction in the TCSR values by NSS can be observed for heterogeneous breast phantoms (C3, H3, and P3). The reduction in TCSR indicates a significant reduction in energy in the late-time
Figure 7.7: The mean Tumour Energy Preservation Ratio (TEPR) of each breast phantom. The TEPR is computed for each radar signal (after processing through both HAR and NSS) and averaged across each breast phantom.

portion of the signals. The HAR algorithm also reduces the late-time response. However, on average the impact of the HAR algorithm on the late-time response remains lesser than that of the NSS algorithm.

The neighbourhood selection method of the NSS algorithm provides a group of signals that contains not only highly similar artifacts but also reflections from interior breast tissues that are also similar. These similar reflections are reduced during the artifact removal process, resulting in lower TCSR values for the NSS algorithm.

The reduction of the late-time response, as indicated by TCSR values, may also result in the reduction of the tumour response. This reduction in the tumour response is due to the fact that the tumour response is also embedded in the late-time response and may also be reduced by the algorithm. This effect will be examined in next subsection.

7.6.1.3 Tumour Energy Preservation Ratio

The TEPR metric quantifies the impact of an artifact removal algorithm on tumour energy. The TEPR value is computed for each radar signal after being processed
through both the NSS and the HAR algorithms, and then averaged across each breast phantom. Figure 7.7 shows the average TEPR computed for each breast phantom.

On average, the NSS algorithm has lower values of TEPR. The lower values of TEPR indicate that the NSS significantly reduces the tumour response. The HAR algorithm also introduces changes in the tumour energy. However, the TEPR values for the HAR algorithm are on average closer to 0 dB suggesting less change in the tumour response.

It is also observed that the tumour energy in some of the signals appears to be greater than the ideal tumour energy. This increase in the tumour energy is due to the imperfect isolation of the tumour response using heterogeneous phantoms, even when ideal artifact removal is used. It is not possible to accurately isolate the tumour response from the response from fibroglandular structures after applying artifact removal algorithms. The TEPR metric for the heterogeneous phantoms is not calculated for this reason.

In summary, signal metrics such as ASR and TCSR indicate that both algorithms significantly suppress artifacts as well as reduce the late-time clutter. The reduction in the late-time signal also reduces similar reflections from glandular structures within the breast.

The NSS algorithm has shown better artifact suppression capability than the HAR algorithm, as indicated by the lower values of ASR. A better late-time clutter suppression capability of the NSS is indicated by the lower values of TCSR. In contrast, the HAR algorithm has shown better tumour response preservation, as indicated by the TEPR values. The difference between the NSS and the HAR TEPR values may have a significant impact due to the coherent addition of tumour responses at the imaging stage. Therefore, the imaging results must also be analysed to further evaluate the performance of both algorithms.

7.6.2 Imaging

The artifact removed signals are processed through the imaging method described in Section 7.3 to produce the final images. The following section describes the
Figure 7.8: Beamformed image of C1 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm.

imaging results and the corresponding imaging metrics computed for each of the breast phantoms.
### Table 7.3: Imaging performance metrics for phantoms scanned with the cylindrical scan pattern

<table>
<thead>
<tr>
<th>Phantom</th>
<th>Algorithm</th>
<th>SCR (dB)</th>
<th>SMR (dB)</th>
<th>Localisation Error (mm)</th>
<th>FWHM (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>HAR</td>
<td>13.4</td>
<td>35.3</td>
<td>2.2</td>
<td>15.7</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>7.2</td>
<td>34.9</td>
<td>9.0</td>
<td>15.3</td>
</tr>
<tr>
<td>C2</td>
<td>HAR</td>
<td>16.5</td>
<td>38.0</td>
<td>4.2</td>
<td>14.5</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>15.6</td>
<td>41.3</td>
<td>6.3</td>
<td>9.7</td>
</tr>
<tr>
<td>Average</td>
<td>HAR</td>
<td>14.9</td>
<td>36.7</td>
<td>3.2</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>11.4</td>
<td>38.1</td>
<td>7.7</td>
<td>12.5</td>
</tr>
</tbody>
</table>

#### 7.6.2.1 Cylindrical Scan Pattern

Figure 7.8 shows the beamformed images of C1 following artifact removal using both HAR and NSS algorithm. The imaging performance metrics computed from C1 and C2 are presented in Table 7.3.

The tumour is successfully detected in the images obtained following both artifact removal algorithms. However, a localisation error and clutter can also be observed in the images. The HAR algorithm has slightly higher average SCR as well as a smaller localisation error compared to the NSS algorithm. Comparatively, the average SMR of the NSS algorithm is moderately higher compared to the HAR algorithm.

The difference in performance of both algorithms is somewhat smaller for the C2 phantom. However, the NSS algorithm has a lower SCR and higher localisation error (9.0 mm) compared to the HAR algorithm in the case of the C1 phantom. One contributing factor towards the poor performance of the NSS algorithm in the C1 case may be the size of the C1 phantom. The cylindrical scan surface has a fixed radius regardless of the size of the breast. Therefore, the distance between skin and antenna locations in the case of the C1 phantom is greater than that for the C2 phantom (larger breast phantom). The larger distance results in more attenuated tumour responses from C2, and further suppression of the tumour response by the artifact removal has a greater impact on the image.
The improved SCR and localisation metrics in images of phantoms scanned with the cylindrical scan configuration with the HAR algorithm suggest better tumour response preservation compared to the NSS algorithm. However, the improved average SMR with the NSS algorithm indicates slightly better artifact suppression compared to the HAR algorithm.

### 7.6.2.2 Hemispherical Scan Pattern

The imaging metrics corresponding to the H1 and H2 phantoms are shown in Table 7.4. Again, the tumour is detected in both phantom images, with small localisation errors, using both artifact removal algorithms. The HAR algorithm has, on average, slightly higher SCR and SMR values than the NSS algorithm. The average localisation error of the HAR algorithm is also smaller than the NSS algorithm. These metrics suggest better performance of the HAR algorithm compared to the NSS algorithm. However, the difference between the SCR and SMR of the both algorithms is less than 2 dB and the difference in the localisation error is only 1 mm.

Analysing the individual phantom images, it is noted that the performance of the HAR algorithm reduces in the case of H2. A higher clutter intensity can be observed in the image produced with the HAR algorithm (Figure 7.9a) compared to the image produced with the NSS algorithm (Figure 7.9b). The FWHM of the H2 phantom is also higher for the HAR algorithm, indicating blurring of the tumour response. The reduction in performance of the HAR algorithm in the case of the H2 phantom may be attributed to lower artifact suppression. The lower artifact suppression is illustrated by the relatively low ASR value by HAR in the case of the H2 phantom, leaving residual artifacts.

Similarly, the performance of the NSS algorithm increases for the H2 phantom. The improved performance is again due to the hemispherical scan configuration that is designed to fit H2 (which is larger in size than H1). The neighbourhood-based selection in the NSS algorithm provides a better estimate of the artifact
7. Artifact Removal for Various Scan Configurations

Figure 7.9: Beamformed image of H2 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm.

when the hemispherical scan surface fits the breast phantom. This improves the performance of the NSS.
Table 7.4: Imaging performance metrics for phantoms scanned with hemispherical scan pattern

<table>
<thead>
<tr>
<th>Phantom</th>
<th>Algorithm</th>
<th>SCR (dB)</th>
<th>SMR (dB)</th>
<th>Localisation Error (mm)</th>
<th>FWHM (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>HAR</td>
<td>17.1</td>
<td>38.7</td>
<td>6.1</td>
<td>6.7</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>9.8</td>
<td>33.4</td>
<td>6.1</td>
<td>6.1</td>
</tr>
<tr>
<td>H2</td>
<td>HAR</td>
<td>9.9</td>
<td>37.4</td>
<td>3.7</td>
<td>10.7</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>13.6</td>
<td>38.2</td>
<td>4.2</td>
<td>7.3</td>
</tr>
<tr>
<td>Average</td>
<td>HAR</td>
<td>13.5</td>
<td>38.1</td>
<td>4.9</td>
<td>8.7</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>11.7</td>
<td>35.9</td>
<td>5.2</td>
<td>6.7</td>
</tr>
</tbody>
</table>

7.6.2.3 Patient-specific Scan Pattern

Both the HAR and the NSS algorithms, on average, perform similarly in terms of all image quality metrics for the patient-specific scan pattern, as shown in Table 7.5.

Figure 7.10 shows the image of P2 following application of the HAR and the NSS algorithms. The tumour is accurately localised in both images. However, the peak tumour intensity appears to be higher in the HAR image, as can be observed in Figure 7.10b.

The higher tumour intensity for the HAR algorithm in this case is attributed to the patient-specific scan pattern, where antennas are placed at an approximately constant distances from the skin. Therefore, all antennas located in the same z-plane have highly similar artifacts. These similar artifacts facilitate the HAR algorithm to better remove the artifact, while also preserving tumour response.

The patient-specific scan pattern also reduces variation within the NSS antenna neighbourhoods. However, the chosen neighbourhood may also have a similar response from the tumour and the interior breast tissues in each signal. Therefore, the response from interior breast tissues may also be reduced while subtracting the early-stage artifact. Therefore, in this case the NSS algorithm has a similar SCR to the HAR algorithm, even though the tumour intensity is lower.
Figure 7.10: Beamformed image of P2 following artifact removal using: (a) HAR algorithm, (b) NSS algorithm.

7.6.2.4 Experimental Evaluation

For both experimental phantoms, the [HAR] algorithm performs better in terms of all imaging metrics except for localisation error, as shown in Table 7.6. The average localisation error is marginally higher (by 0.3 mm) for the [HAR] algorithm.
Table 7.5: Imaging performance metrics for phantoms scanned with a patient-specific scan pattern

<table>
<thead>
<tr>
<th>Phantom</th>
<th>Algorithm</th>
<th>SCR (dB)</th>
<th>SMR (dB)</th>
<th>Localisation Error (mm)</th>
<th>FWHM (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>HAR</td>
<td>11.5</td>
<td>37.1</td>
<td>2.8</td>
<td>9.9</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>12.2</td>
<td>35.3</td>
<td>2.2</td>
<td>9.0</td>
</tr>
<tr>
<td>P2</td>
<td>HAR</td>
<td>12.9</td>
<td>36.4</td>
<td>4.2</td>
<td>7.3</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>12.0</td>
<td>31.3</td>
<td>4.1</td>
<td>8.7</td>
</tr>
<tr>
<td>Average</td>
<td>HAR</td>
<td>12.2</td>
<td>36.8</td>
<td>3.5</td>
<td>8.6</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>12.1</td>
<td>33.3</td>
<td>3.2</td>
<td>8.9</td>
</tr>
</tbody>
</table>

compared to the NSS algorithm.

The imaging results for the experimental phantom E2, following both artifact removal algorithms, are shown in Figure 7.11. The tumour is localised in both images. However, the overall clutter, as well as peak clutter intensity, also appears to be higher in the image produced using the NSS algorithm.

The overall imaging performance metrics indicate that the HAR performs better in the case of experimental phantoms. The improved performance may be largely attributed to the patient-specific scan pattern, which improves the similarity of skin responses at antennas located at the same elevation. The similarity of the artifact allows the HAR algorithm to better estimate and remove the artifact while preserving the tumour response.

Table 7.6: Imaging performance metrics for experimental phantoms

<table>
<thead>
<tr>
<th>Phantom</th>
<th>Algorithm</th>
<th>SCR (dB)</th>
<th>SMR (dB)</th>
<th>Localisation Error (mm)</th>
<th>FWHM (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>HAR</td>
<td>12.1</td>
<td>28.5</td>
<td>17.0</td>
<td>19.0</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>6.3</td>
<td>25.9</td>
<td>11.2</td>
<td>15.5</td>
</tr>
<tr>
<td>E2</td>
<td>HAR</td>
<td>6.9</td>
<td>27.5</td>
<td>6.5</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>2.3</td>
<td>27.5</td>
<td>8.1</td>
<td>19.7</td>
</tr>
<tr>
<td>Average</td>
<td>HAR</td>
<td>9.5</td>
<td>28.0</td>
<td>11.8</td>
<td>17.0</td>
</tr>
<tr>
<td></td>
<td>NSS</td>
<td>4.3</td>
<td>26.8</td>
<td>9.6</td>
<td>17.6</td>
</tr>
</tbody>
</table>
Figure 7.11: Beamformed image of E2 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm.

7.6.2.5 MRI-based Heterogeneous Phantoms

Figure 7.12-7.14 show the images of MRI-based heterogeneous phantoms obtained after the application of each artifact removal algorithm. The presence of the tumour can be observed in the breast slices in images of H3 and P3, along with other
Figure 7.12: Beamformed image of C3 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm.

responses from fibroglandular structures. However, the tumour intensity is weak and clutter is dominant, particularly in the images of C3.

The clutter due to fibroglandular tissues is significantly higher in images produced with the HAR algorithm when compared with NSS images. The lower level
Figure 7.13: Beamformed image of H3 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm.

The focus of this work is to evaluate the artifact removal algorithms by exclusively...
7. Artifact Removal for Various Scan Configurations

Figure 7.14: Beamformed image of P3 following artifact removal using the: (a) HAR algorithm, (b) NSS algorithm.

quantifying the clutter due to residual artifacts. However, the clutter in the images of the heterogeneous breast is not only associated with the residual artifacts. It may also be attributed to reflections from fibroglandular structures, propagation path inaccuracies and the ability of the imaging algorithm to suppress incoherent
reflections. Therefore, due to ambiguities in the identification of the sources of clutter, imaging quality metrics such as SCR and SMR are not calculated for the heterogeneous breast phantom. However, the imaging results demonstrate the efficacy of the algorithms in reducing skin reflections from heterogeneous breast phantoms. The results can be improved with more advanced imaging algorithms that have better clutter suppression capabilities, such as those reported in [54], [114].

Table 7.7: Summary of imaging performance metrics for the both simulated and experimental phantoms

<table>
<thead>
<tr>
<th>Scan Configuration</th>
<th>SCR (dB)</th>
<th>SMR (dB)</th>
<th>Localisation Error (mm)</th>
<th>FWHM (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HAR</td>
<td>NSS</td>
<td>HAR</td>
<td>NSS</td>
</tr>
<tr>
<td>Cylindrical</td>
<td>14.9</td>
<td>11.4</td>
<td>36.7</td>
<td>38.1</td>
</tr>
<tr>
<td>Hemispherical</td>
<td>13.5</td>
<td>11.7</td>
<td>38.1</td>
<td>35.9</td>
</tr>
<tr>
<td>Patient-specific</td>
<td>12.2</td>
<td>12.1</td>
<td>36.8</td>
<td>33.3</td>
</tr>
<tr>
<td>Experimental</td>
<td>9.5</td>
<td>4.3</td>
<td>28.0</td>
<td>26.8</td>
</tr>
</tbody>
</table>

The imaging performance metrics for all breast phantoms and scan configurations are summarised in Table 7.7. In summary, the HAR and the NSS algorithms have very similar average SCR and SMR values for the phantoms scanned with the cylindrical and hemispherical scan pattern. Comparatively, the HAR algorithm has marginally higher average SCR and lower localisation error than the NSS algorithm. The NSS algorithm has an average localisation error that is almost twice that of the HAR algorithm for the cylindrical scan pattern. This error may be attributed to the distortion introduced by the NSS algorithm in the tumour response. However, the NSS algorithm outperforms the HAR algorithm for the hemispherical scan configurations when the breast size matches the geometry of the hemispherical scan configuration. Both algorithms have similar performance in terms of imaging metrics when applied to simulated breast phantoms scanned with the patient-specific scan pattern. In comparison, the HAR algorithm has better performance for the experimental phantoms than the NSS algorithm.

Finally, in the case of the MRI-based phantom, both algorithms reduce the skin-artifacts. However, strong responses from healthy breast tissues are also
present along with the tumour response. The NSS images have less clutter from interior tissues since the NSS algorithm reduces the responses from the interior of the breast in contrast to the HAR algorithm that tends to preserve responses from the breast interior.

7.7 Conclusions

In this chapter, two promising artifact removal algorithms developed for radar-based microwave imaging of the breast have been evaluated in various challenging test scenarios. Numerical as well as experimental breast phantoms with different tumours included at challenging locations (e.g. close to the skin), and different scan configurations have been used to compare the algorithms. The scan configurations used in this study are the most common configurations used in microwave breast imaging prototypes. Therefore, the results can be broadly generalised across most prototype systems. Results indicate that both the NSS and the HAR algorithms effectively reduce the skin-artifacts across all breast phantoms and scan configurations. The responses from interior breast tissues that include healthy as well as cancerous tissues are also reduced by both algorithms. However, the HAR algorithm has been shown to better preserve responses from interior breast tissues. In terms of imaging quality metrics, both algorithms produce similar quality images across all scan configurations and simulated phantoms. However, the HAR algorithm produces better quality images for experimental breast phantoms.

It should also be noted that the ability of the NSS algorithm to reduce the responses from the interior breast tissues is particularly useful in heterogeneous scenarios. This is because it facilitates the imaging algorithm to produce images with less clutter due to fibroglandular responses. However, the tumour response will also be reduced using the NSS algorithm.

In the following chapter, the performance of various imaging algorithms will be assessed using the patient data.
8

Imaging of Patients

8.1 Introduction

Chapters 3-7 focused on the development and evaluation of artifact removal algorithms to address a critical signal processing challenge of reducing early-stage artifacts for CMI of the breast. Another important signal processing challenge in reconstructing high quality breast images using CMI is the image reconstruction algorithm itself. An effective image reconstruction algorithm provides an accurate localisation of tumours, while suppressing clutter due to healthy breast tissues and any residual artifacts from preprocessing.

Several image reconstruction algorithms for CMI have been developed over the last two decades [35], [39], [40], [45–49], [51], [53], [117], [118]. These algorithms have been categorised as DI beamforming and DA beamforming algorithms in the literature [108]. Both DI and DA beamforming algorithms are based on the principle of coherent addition of backscattered radar signals, which are collected after illuminating the breast with UWB pulses. In DI beamforming algorithms, coherent addition is performed based on an assumed propagation model. However, DA algorithms estimate the propagation model from the received signals and apply compensation factors based on this estimated channel model. Several studies have been performed to evaluate the performance of both DI and DA beamforming algorithms.
algorithms using a variety of numerical and physical breast models [48], [51], [54]–[59], [119]. A detailed review of these performance evaluation studies was presented in Section 2.6.

In summary, the performance of both DI and DA algorithms have often been evaluated using the following: a limited set of beamforming algorithms [48], simplified breast phantoms [51], [55], [56], [177], and an idealised artifact removal algorithm, while ignoring the impact of realistic artifact removal [54], [57], [58]. One recent study applied multiple imaging algorithms to clinical data from healthy volunteers [59]. The volunteers had no breast cancer and therefore tumour responses were artificially introduced in the acquired data. Differential signals with only induced tumour responses were used for imaging. The results from this clinical investigation are based on several assumptions such as the availability of accurate tumour signature templates and of the baseline measurements. Therefore, these results may not be generalisable to the diagnostic application where baseline measurements are not available, and where an accurate estimation of the tumour signature template in an unknown breast density is not possible. In conclusion, the current literature lacks a comprehensive evaluation of a variety of imaging algorithms in realistic clinical scenarios.

In this chapter, the performance of a variety of DI and DA algorithms is evaluated using clinical patient data. The algorithms examined in this study include the following:

- **Delay-And-Sum** (DAS),
- **Improved Delay-And-Sum** (IDAS),
- **Delay-Multiply-And-Sum** (DMAS),
- **Coherence Factor based DAS** (CF-DAS),
- **Channel Ranked DAS** (CR-DAS),
- **Robust Capon Beamformer** (RCB).
The novelty of this study is two-fold: firstly, a comprehensive set of both DI and DA beamforming algorithms is examined; secondly, these algorithms are evaluated together for the first time on both clinical patient data and with a non-idealised artifact removal algorithm. The patient data used in this study was obtained from the first patient study conducted at the University of Calgary \[145\]. The patients were scanned using the first generation TSAR prototype \[61\]. In the original publication \[169\], breast images were reconstructed using the traditional DAS algorithm. The images reconstructed with the DAS algorithm were consistent with clinical information in most cases. However, not all lesions were detected. This current study aims to evaluate more advanced imaging algorithms on the same patient data. Improved clutter suppression capabilities of the more advanced CMI algorithms are expected to improve upon the DAS imaging results for the University of Calgary patient study reported in \[145\].

The remainder of this chapter is organised as follows: Section 8.2 describes the patient details, patient scanning and preprocessing of the scanned data; and Section 8.3 presents the discussion of all results. Finally, conclusions are presented in Section 8.4.

8.2 Patient Scanning and Preprocessing

In this section, details of patients, the patient scanning process, and the preprocessing of scanned data is detailed.

8.2.1 Patient Information

The patient data used in this study comes from the microwave imaging patient study conducted at the University of Calgary \[145\]. The patient recruitment and the patient scanning using the TSAR prototype are detailed in \[145\]. An overview of the patient scanning process is described in this section. A total of 8 patients were scanned using the TSAR system. Most of the patients recruited into the study had a suspicious region in one breast, which was identified through a mammogram or a clinical examination. The breast with the suspicious region was scanned with
the TSAR system. Prior to the TSAR scan, each patient was also scanned with a contrast enhanced MRI to aid in interpretation of the TSAR images.

This chapter considers 5 of the total 8 patients, where clinical images of patients either clearly identified benign or malignant lesions, or found no disease to be present. The three patients excluded from this study had some of the malignancies removed via biopsy, and therefore, the microwave images were challenging to interpret due to scar tissue at the biopsy sites in addition to any remaining malignancies. Table 8.1 summarises the important clinical information of each patient including patient age, breast density, and disease type.

8.2.2 Patient Scanning

The first generation TSAR prototype used for the patient scanning is described in [61]. A detailed review of the prototype has been presented in Section 2.8.

The prototype features a monostatic data acquisition system with an UWB BAVA-D antenna [144] that is mounted on a positioning arm. In order to scan a breast, the measurements are collected by moving the arm vertically while the entire tank rotates. This results in a cylindrical scan configuration, where each measurement is taken by positioning the sensor at a fixed radius from the centre of the tank. The sensor positioning is controlled by actuating stepper motors using custom software. The prototype also has a laser system mounted on the positioning arm. The collected laser data is used to reconstruct the breast surface that can later be used to improve the reconstructed microwave images. The system also has a digital camera to monitor the sensor positioning and the breast during the scanning process.

During the patient scan, the BAVA-D antenna was vertically moved in a step of 5-10 mm between the nipple and chest wall of the breast. For each vertical position, multiple measurements were collected around the breast. The number of vertical positions (rows) for each patient were decided based on the vertical extent of the breast. The extent of breast was estimated using the images acquired from the digital camera. For each patient, up to 200 measurements were collected.
8. Imaging of Patients

<table>
<thead>
<tr>
<th>Patient</th>
<th>Age</th>
<th>Breast imaged</th>
<th># of rows</th>
<th>Antennas per row</th>
<th>Breast density</th>
<th>Disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient 1</td>
<td>53</td>
<td>R</td>
<td>6</td>
<td>30</td>
<td>Heterogeneous</td>
<td>Malignancy</td>
</tr>
<tr>
<td>Patient 2</td>
<td>64</td>
<td>L</td>
<td>8</td>
<td>20</td>
<td>Extremely dense</td>
<td>Benign</td>
</tr>
<tr>
<td>Patient 3</td>
<td>35</td>
<td>L</td>
<td>9</td>
<td>20</td>
<td>Scattered/heterogeneous</td>
<td>Malignancy</td>
</tr>
<tr>
<td>Patient 4</td>
<td>44</td>
<td>L</td>
<td>5</td>
<td>30</td>
<td>Heterogeneous</td>
<td>No disease</td>
</tr>
<tr>
<td>Patient 5</td>
<td>32</td>
<td>L</td>
<td>6</td>
<td>30</td>
<td>Heterogeneous</td>
<td>No disease</td>
</tr>
</tbody>
</table>

The measurements were acquired using a VNA at 1601 frequency points over the range of 50 MHz to 15 GHz with port power of -5 dBm. The IF bandwidth of 1 kHz and an average of three measurements was used to reduce the noise floor. For the calibration of the system, another set of measurements were collected without the patient present. The second set of measurements were collected at the same locations that were used to collect the patient measurements. This data was called “calibration” scan.

8.2.3 Preprocessing

The frequency-domain data acquired from the VNA was preprocessed prior to imaging. Firstly, the calibration scan was subtracted from the patient scan. Next, the frequency-domain data was weighted with a differentiated Gaussian pulse, and converted to the time-domain using an inverse Chirp-Z transform [178]. The centre frequency of the pulse was 4 GHz and the full-width half-maximum frequency content was between 1.3 and 7.6 GHz. A phase-shift was also introduced in the calibrated data to compensate for the antenna aperture location. The resultant time-domain signals were then processed through the NSS algorithm for skin subtraction [172]. The NSS algorithm was detailed in Section 7.2.1. The NSS algorithm estimates the artifact at a particular antenna from a neighbourhood of antennas, and the estimated artifact is then subtracted from the target antenna.
8.3 Results

In the current study, the preprocessed patient data is used to reconstruct the breast images of patients using the DAS, IDAS, CF-DAS, DMAS, CR-DAS and RCB imaging algorithms. An average breast permittivity of $\epsilon_r = 9$ was used to estimate the propagation speed and the corresponding distance travelled in the interior of the breast during image reconstruction. The reconstruction results obtained from each individual patient using different imaging algorithms are described in this section.

Microwave images obtained from each imaging algorithm are shown for each patient in Figures 8.2-8.8. Tables 8.2-8.6 summarise the analysis and interpretation of the microwave images of each patient. Information contained in each column of tables is described below:

- The first column in each table lists the imaging algorithm used to image the patient.

- The second column lists clinically identified (CI) regions of interest (ROI) that were detected through either clinical imaging or clinical examination and are expected to be detected in the microwave images. Any additional high intensity (HI) regions identified in microwave images (MI) are also listed in this column.

- The third column indicates whether CI-ROIs were detected in microwave images (MI).

- The fourth column of the table lists the SMR of each high intensity region detected in the microwave images. The SMR is a measure of the quality of the beamformed image that provides a measure of separation between the ROI and the background clutter. It is defined as the ratio of the average intensity of the ROI to the average intensity of the overall 3D image.

- The fifth column lists the FWHM of each high intensity region detected in the microwave images. The FWHM may be used to estimate the extent of
the ROI in the image. The FWHM is defined as twice the distance from peak intensity in the ROI to the point where intensity of ROI drops by half. The FWHM is computed by growing a region around the centroid of the ROI until the ROI intensity drops by half. The twice of the average Euclidean distance from the centroid of the ROI to the end of the region is estimated to be the FWHM.

The last column ranks the performance of each algorithm in terms of the detection of the CI-ROI and the quality of the image.

The results of each individual patient are discussed in the following sections.

Patient 1

The mammogram indicated the presence of a 10 mm lesion at the 4 o’clock radian in the right breast of this patient. The MRI report showed the lesion at 5 o’clock, and a second possibly benign lesion at 7 o’clock. An MR image of the patient is shown in Figure 8.1. The microwave images obtained from each imaging algorithm are shown in Figure 8.2 and the analysis of each image is presented in Table 8.2. The image produced with DAS (Figure 8.2a) shows three responses in the image. The dominant response $R_1$ at around the 5 o’clock position in the coronal slice corresponds to the location of the malignant lesion. The second response $R_2$ near to the 7 o’clock radian corresponds to the benign lesion, and the third response $R_3$ at approximately 11 o’clock corresponds to the fibroglandular concentration.

The image obtained with the IDAS algorithm shows only one response $R_2$, which is dominant in the image. The dominant response corresponds to the location of the benign lesion. The other two responses $R_1$ and $R_3$ are low in intensity and are not clearly visible in the image. The CF-DAS algorithm also showed three responses with a dominant response $R_2$ at the location of the benign lesion. The response $R_1$, which corresponds to the malignant lesion is also present in the image. However, the intensity is much lower than both $R_2$ and $R_3$. The DMAS image shows all three responses. The location of the all three responses in the DMAS image are
consistent with the DAS image, and are also consistent with the clinical information. The CR-DAS shows two responses, $R_1$ and $R_2$, where $R_2$ is the dominant response, which corresponds to the benign lesion. The dominant response in the RCB image is closer to the skin and does not correspond to any of the responses identified in images produced with other algorithms.

In terms of image quality, the IDAS, CF-DAS and CR-DAS have improved the SMR of $R_2$ when compared to DAS, which corresponds to the benign lesion. The DMAS algorithm has improved the SMR of all lesions. All algorithms have less average clutter compared to the DAS algorithm. However, DMAS has not only much less average clutter than all other algorithms but the dominant response also corresponds to the location of the malignant lesion, with a much higher SMR value than the SMR achieved by the DAS algorithm. DMAS also has consistent locations of all three responses with the DAS image and clinical information. The presence of a dominant scatterer near the skin in the RCB image indicates that the RCB has most likely enhanced early-time clutter.

Table 8.2 summarises the detection and the image quality metrics computed for each algorithm. The algorithms are ranked based on the detection of a malignant tumour and the SMR of the malignant tumour. DMAS has detected the malignant tumour with the highest SMR compared to all other algorithms. Therefore, it is
Figure 8.2: Microwave images of Patient 1 for a range of different imaging algorithms.
Figure 8.2: Microwave images of Patient 1 for a range of different imaging algorithms.
Figure 8.2: Microwave images of Patient 1 for a range of different imaging algorithms.
### Table 8.2: Summary of the analysis of Patient 1 microwave images.

<table>
<thead>
<tr>
<th>Imaging Algo.</th>
<th>ROI</th>
<th>CI-ROI present in MI?</th>
<th>SMR (dB)</th>
<th>FWHM (dB)</th>
<th>Algo. Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAS CI</td>
<td>Malignant lesion ($R_1$)</td>
<td>Yes</td>
<td>23.04</td>
<td>32.57</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Benign lesion ($R_2$)</td>
<td>Yes</td>
<td>21.32</td>
<td>31.19</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fibroglanular concentration ($R_3$)</td>
<td>Yes</td>
<td>21.39</td>
<td>36.07</td>
<td></td>
</tr>
<tr>
<td>IDAS CI</td>
<td>Malignant lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Benign lesion ($R_2$)</td>
<td>Yes</td>
<td>49.92</td>
<td>36.07</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fibroglanular concentration ($R_3$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>CFDAS CI</td>
<td>Malignant lesion ($R_1$)</td>
<td>Yes</td>
<td>25.80</td>
<td>27.14</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Benign lesion ($R_2$)</td>
<td>Yes</td>
<td>29.55</td>
<td>17.23</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fibroglanular concentration ($R_3$)</td>
<td>Yes</td>
<td>27.16</td>
<td>23.62</td>
<td></td>
</tr>
<tr>
<td>DMAS CI</td>
<td>Malignant lesion ($R_1$)</td>
<td>Yes</td>
<td>39.60</td>
<td>20.04</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Benign lesion ($R_2$)</td>
<td>Yes</td>
<td>36.27</td>
<td>23.22</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fibroglanular concentration ($R_3$)</td>
<td>Yes</td>
<td>37.82</td>
<td>17.55</td>
<td></td>
</tr>
<tr>
<td>CRDAS CI</td>
<td>Malignant lesion ($R_1$)</td>
<td>Yes</td>
<td>23.88</td>
<td>31.82</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Benign lesion ($R_2$)</td>
<td>Yes</td>
<td>27.34</td>
<td>29.20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fibroglanular concentration ($R_3$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>RCB CI</td>
<td>Malignant lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Benign lesion ($R_2$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fibroglanular concentration ($R_3$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>HI region near to chest wall ($R_4$)</td>
<td>Yes</td>
<td>-</td>
<td>31.79</td>
<td>15.60</td>
</tr>
</tbody>
</table>
ranked 1. The [DAS] and [RCB] have failed to detect the malignant tumour. Hence, both of these algorithms have not been considered for ranking.

**Patient 2**

The mammogram of this patient reported a fibroadenolipoma of several centimetres in diameter, in the inner lower quadrant of the left breast (Figure 8.3). Fibroadenolipoma is a benign lesion formed with fibrous, glandular and fatty tissues encapsulated in a thin layer of connective tissue.

![Mammogram of Patient 2 (© 2013 IEEE. Reprinted, from [145]).](image)

**Figure 8.3:** Mammogram of Patient 2 (© 2013 IEEE. Reprinted, from [145]).

The microwave images of this patient are shown in Figure 8.4 and the analysis of the images is summarised in Table 8.3. The [DAS] image shows several high intensity responses. However, the dominant response $R_1$ is observed in the lower inner quadrant of the breast and is consistent with the clinical information. The dominant response in the [IDAS] image is closer to the chest wall and does not correspond to any known lesion in the breast. Similarly, the dominant response in the [CF-DAS] image is located in the lower outer quadrant and does not correspond to the clinically identified lesion. Similar to the [DAS] image, the [DMAS] image shows the dominant response in the lower inner quadrant of the breast. The [CR-DAS] has also produced
Figure 8.4: Microwave images of Patient 2 for a range of different imaging algorithms.
Figure 8.4: Microwave images of Patient 2 for a range of different imaging algorithms.
8. Imaging of Patients

Figure 8.4: Microwave images of Patient 2 for a range of different imaging algorithms.
Table 8.3: Summary of the analysis of Patient 2 microwave images.

<table>
<thead>
<tr>
<th>Imaging Algo.</th>
<th>ROI</th>
<th>CI-ROI present in MI?</th>
<th>SMR (dB)</th>
<th>FWHM (dB)</th>
<th>Algo. Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAS</td>
<td>CI Benign lesion ($R_1$)</td>
<td>Yes</td>
<td>26.41</td>
<td>13.60</td>
<td>3</td>
</tr>
<tr>
<td>IDAS</td>
<td>CI Benign lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI HI region close to the chest wall ($R_2$)</td>
<td>-</td>
<td>59.56</td>
<td>5.00</td>
<td></td>
</tr>
<tr>
<td>CFDAS</td>
<td>CI Benign lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI HI region at the lower outer quadrant of the breast ($R_3$)</td>
<td>-</td>
<td>35.48</td>
<td>10.72</td>
<td></td>
</tr>
<tr>
<td>DMAS</td>
<td>CI Benign lesion ($R_1$)</td>
<td>Yes</td>
<td>45.66</td>
<td>8.78</td>
<td>1</td>
</tr>
<tr>
<td>CRDAS</td>
<td>CI Benign lesion ($R_1$)</td>
<td>Yes</td>
<td>30.06</td>
<td>13.34</td>
<td>2</td>
</tr>
<tr>
<td>RCB</td>
<td>CI Benign lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI HI region below the nipple ($R_4$)</td>
<td>-</td>
<td>38.03</td>
<td>6.96</td>
<td></td>
</tr>
</tbody>
</table>

The images produced with the DAS, DMAS and CR-DAS algorithms are similar in terms of location of the dominant response $R_1$. The dominant response in the RCB image is observed below the nipple and does not correspond to the known location of the fibroadenolipoma.

The images produced with the DAS, DMAS and CR-DAS algorithms are similar in terms of location of the dominant response and are also consistent with the clinical information. However, both the CR-DAS and the DMAS provide an improved SMR of the dominant response compared to the DAS algorithm, with the best SMR achieved with the DMAS algorithm. The IDAS, CF-DAS and the RCB algorithms suppress the average clutter in the images. However, the location of the dominant response is not consistent with the known location of the fibroadenolipoma.

Table 8.3 summarises the detection and the image quality metrics computed for each algorithm. The algorithms are ranked based on the detection of the benign lesion (the only CI-ROI) and the SMR of the benign lesion. The DAS, DMAS and
**CR-DAS** algorithms have detected the benign lesion, with **DMAS** providing highest SMR. Therefore, it is ranked first. The **IDAS** **CF-DAS** and **RCB** algorithms have not detected the lesion and therefore have not been considered in the ranking.

**Patient 3**

The **MRI** report of this patient showed enhancements from the 2 o’clock to 6 o’clock radians, and a focal mass located near the nipple (Figure 8.5). The mammogram showed extensive microcalcifications around the 3 o’clock position. The patient was later diagnosed with the **IDC** of size 14 x 2 x 2 cm in the upper outer quadrant of the breast.

![Figure 8.5: Magnetic Resonance Imaging (MRI) scan of Patient 3 (© 2013 IEEE. Reprinted, from [145]).](image)

The microwave images of this patient are shown in Figure 8.6. The analysis of each image is presented in Table 8.4. The **DAS** image shows two responses $R_1$ and $R_2$ near the nipple. These responses may correspond to a focal mass reported in the **MRI** report. The **IDAS** image does not show the responses $R_1$ and $R_2$ previously observed in the **DAS** image. The dominant response, $R_3$, in the **IDAS** image can be observed at approximately 3 o’clock (in the coronal view) and may correspond to the **IDC**. The **CF-DAS** image does show two responses $R_1$ and $R_2$ near the nipple. However, the dominant response $R_4$ is displaced compared to the **DAS** image. The **DMAS** image also shows two responses $R_1$ and $R_2$, as previously observed in the **DAS** image. The **CR-DAS** shows a dominant response at approximately 4 o’clock...
8. Imaging of Patients

Figure 8.6: Microwave images of Patient 3 for a range of different algorithms.

(a) Microwave image of Patient 3 reconstructed with DAS

(b) Microwave image of Patient 3 reconstructed with IDAS
Figure 8.6: Microwave images of Patient 3 for a range of different algorithms.
Figure 8.6: Microwave images of Patient 3 for a range of different algorithms.
Table 8.4: Summary of the analysis of Patient 3 microwave images.

<table>
<thead>
<tr>
<th>Imaging Algo.</th>
<th>ROI</th>
<th>CI-ROI present in MI?</th>
<th>SMR (dB)</th>
<th>FWHM (dB)</th>
<th>Algo. Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAS CI</td>
<td>Malignant tumour</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>4</td>
</tr>
<tr>
<td>DAS CI</td>
<td>Focal mass (R₁)</td>
<td>Yes</td>
<td>28.38</td>
<td>17.11</td>
<td></td>
</tr>
<tr>
<td>DAS MI</td>
<td>HI region near to the nipple (R₂). Probably part of the focal mass.</td>
<td>Yes</td>
<td>24.62</td>
<td>20.15</td>
<td></td>
</tr>
<tr>
<td>IDAS CI</td>
<td>Malignant tumour (R₃)</td>
<td>Yes</td>
<td>58.74</td>
<td>5.74</td>
<td></td>
</tr>
<tr>
<td>IDAS CI</td>
<td>Focal mass (R₁)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>CFDAS CI</td>
<td>Malignant tumour</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>3</td>
</tr>
<tr>
<td>CFDAS CI</td>
<td>Focal mass (R₁)</td>
<td>Yes</td>
<td>38.89</td>
<td>11.35</td>
<td></td>
</tr>
<tr>
<td>CFDAS MI</td>
<td>HI region near to the nipple (R₄).</td>
<td>-</td>
<td>43.89</td>
<td>11.05</td>
<td></td>
</tr>
<tr>
<td>DMAS CI</td>
<td>Malignant tumour</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td>DMAS CI</td>
<td>Focal mass (R₁)</td>
<td>Yes</td>
<td>52.11</td>
<td>11.58</td>
<td></td>
</tr>
<tr>
<td>CRDAS CI</td>
<td>Malignant tumour</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>CRDAS CI</td>
<td>Focal mass (R₁)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>CRDAS MI</td>
<td>HI region at 4 o'clock (R₅)</td>
<td>-</td>
<td>30.75</td>
<td>20.92</td>
<td></td>
</tr>
<tr>
<td>RCB CI</td>
<td>Malignant tumour</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>RCB CI</td>
<td>Focal mass (R₁)</td>
<td>No</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>RCB MI</td>
<td>HI region near to the nipple (R₄)</td>
<td>-</td>
<td>56.78</td>
<td>9.06</td>
<td></td>
</tr>
</tbody>
</table>

in the lower outer quadrant of the breast and does not correspond to any clinically identified lesion. The RCB image is similar to the CF-DAS image in terms of the dominant response location, but it only shows a single dominant response, R₄.

The image produced with the IDAS has a dominant response at 3 o’clock, where it can possibly correspond to the IDC. The images obtained with the DAS, CF-DAS, DMAS and the RCB algorithms show responses near the nipple. As described earlier, these responses may correspond to the focal mass reported in the MRI. The
images produced by DAS and DMAS are similar in terms of dominant response location, but DMAS has higher SMR of the dominant response and demonstrates better clutter suppression. The RCB image also has the dominant response location closer to the nipple. Except IDAS none of these algorithms have detected the IDC regions, as none of the dominant responses correspond to the IDC location.

Table 8.4 summarises the detection and the image quality metrics computed for each algorithm. The IDAS algorithm may have detected the IDC and also has shown the highest SMR. Therefore, IDAS has been ranked first. The other algorithms DAS, CF-DAS, DMAS, CR-DAS and RCB have not detected the IDC but they have shown the presence of the focal mass, which was reported in MRI. Therefore, the ranking of other algorithms has been based on the detection of the focal mass and the SMR of the focal mass. Again, DMAS has detected the presence of the focal mass with the highest SMR and therefore has been ranked second.

Patient 4

The mammography and the Ultrasound report showed a lesion of 11 x 7 mm in size at the 10 o’clock position in the left breast. The lesion was later found to be benign with fat necrosis. Figure 8.7 shows the microwave images produced with all imaging algorithms, and the analysis of the microwave images is presented in Table 8.5.

The DAS images shows a dominant response $R_1$ at a location that could possibly correspond to the location of the lesion. Several other responses with similar high intensities can also be observed in the DAS image. The IDAS image shows the dominant response $R_2$ at a location that does not correspond to the lesion location. The response $R_2$ is also dominant in the CF-DAS image. The $R_1$ lesion can also be observed in the CF-DAS image, but it is relatively weaker in comparison to $R_2$. The DMAS image shows the dominant response near to the 10 o’clock position, as was previously observed in the DAS image. The dominant response $R_3$ in the CR-DAS image is located closer to the chest wall and does not correspond to any clinically detected lesion. Similar to IDAS and CF-DAS the RCB image shows dominant response $R_2$ that does not correspond to the clinically detected lesion.
Figure 8.7: Microwave images of Patient 4 for a range of different algorithms.
Figure 8.7: Microwave images of Patient 4 for a range of different algorithms.
8. Imaging of Patients

(e) Microwave image of Patient 4 reconstructed with CR-DAS

(f) Microwave image of Patient 4 reconstructed with RCB

**Figure 8.7:** Microwave images of Patient 4 for a range of different algorithms.
Table 8.5: Summary of the analysis of Patient 4 microwave images.

<table>
<thead>
<tr>
<th>Imaging Algo.</th>
<th>ROI</th>
<th>CI-ROI present in MI?</th>
<th>SMR (dB)</th>
<th>FWHM (dB)</th>
<th>Algo. Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAS</td>
<td>CI</td>
<td>Benign lesion ($R_1$)</td>
<td>Yes</td>
<td>22.04</td>
<td>25.40</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td>HI region near to 2’o clock ($R_2$)</td>
<td>-</td>
<td>54.55</td>
<td>11.18</td>
</tr>
<tr>
<td>IDAS</td>
<td>CI</td>
<td>Benign lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td>HI region near to 2’o clock ($R_2$)</td>
<td>-</td>
<td>27.26</td>
<td>28.17</td>
</tr>
<tr>
<td>CFDAS</td>
<td>CI</td>
<td>Benign lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td>HI region near to 2’o clock ($R_2$)</td>
<td>-</td>
<td>29.60</td>
<td>24.51</td>
</tr>
<tr>
<td>DMAS</td>
<td>CI</td>
<td>Benign lesion ($R_1$)</td>
<td>Yes</td>
<td>39.81</td>
<td>11.04</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td>HI region closer to the chest wall ($R_3$)</td>
<td>-</td>
<td>33.15</td>
<td>15.30</td>
</tr>
<tr>
<td>CRDAS</td>
<td>CI</td>
<td>Benign lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td>HI region near to 2’o clock ($R_2$)</td>
<td>-</td>
<td>33.15</td>
<td>15.30</td>
</tr>
<tr>
<td>RCB</td>
<td>CI</td>
<td>Benign lesion ($R_1$)</td>
<td>No</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td>HI region near to 2’o clock ($R_2$)</td>
<td>-</td>
<td>33.15</td>
<td>15.30</td>
</tr>
</tbody>
</table>

The **DAS** and the **DMAS** images are similar in terms of location of the dominant response. However, the **DMAS** image has much less clutter than the **DAS** image. **DMAS** also provides an improved **SMR** for the dominant response. In comparison, the **IDAS**, **CF-DAS** and **RCB** images also have much less clutter and a higher **SMR** of the dominant responses when compared to **DAS**. However, the dominant response location is inconsistent with the location of the lesion for these three algorithms. The presence of the dominant response closer to the chest wall in the **CR-DAS** image suggests that **CR-DAS** has enhanced the clutter as this undesired response does not appear in the images produced with any other algorithm.

Table 8.5 summarises the detection and image quality metrics computed for each algorithm. **DAS** and **DMAS** are the only algorithms that have shown the presence of the benign lesion, with **DMAS** providing the highest **SMR** value. The other algorithms have not detected the lesion and therefore have not been considered in the rankings.
Patient 5

Patient 5 had a heterogeneously dense breast, as indicated by the mammography report. The report also indicated a small concentration of fibroglandular tissue on the inner side of the breast and more glandular tissue on the outer side. However, no breast disease was found. The microwave image produced with the DAS (Figure 8.8a) algorithm shows a dominant response $R_1$ near to the 8 o’clock position in the coronal slice. Other weaker responses can also be observed in the DAS image. The dominant response in the image can be attributed to the concentration of fibroglandular tissues, as mentioned in the mammography report. The IDAS image shows two high intensity responses. The response $R_1$ is the same response that was dominant in the DAS image. However, a second response $R_2$ has appeared near to 9 o’clock, and this response $R_2$ is the dominant response in the IDAS image. The CF-DAS and the DMAS images show only one response, $R_1$. With both CF-DAS and DMAS $R_1$ is not only the dominant response but comparatively the intensity of the second response $R_2$ is much weaker. Both responses, $R_1$ and $R_2$, are present in the CR-DAS image, with $R_2$ being the dominant response. The dominant response $R_3$ in RCB does not correspond to any clinically detected lesion.

Both CF-DAS and DMAS significantly improved the SMR of the dominant response $R_1$. The higher values of SMR indicate that both algorithms have suppressed clutter in the images. The analysis of the images also indicates that both of the algorithms have not only suppressed the average clutter, but the response $R_2$ (that does not correspond to any clinically known region of interest) has also been significantly reduced. The IDAS algorithm improves the SMR of the response $R_1$ but it has also improved the SMR of the response $R_2$, which was much lower in the DAS image. CR-DAS has produced a similar image to IDAS by improving the SMR of $R_2$ and reducing the SMR of $R_1$. Finally, RCB exhibits high intensity regions that are not consistent with images produced with other algorithms.

Table 8.6 summarises the detection and image quality metrics computed for each algorithm. There was no tumour present in this patient and the only CI-ROI in this patient was a concentration of fibroglandular tissues. Most algorithms have
8. Imaging of Patients

(a) Microwave image of Patient 5 reconstructed with DAS

(b) Microwave image of Patient 5 reconstructed with IDAS

Figure 8.8: Microwave images of Patient 5 for a range of different algorithms.
(c) Microwave image of Patient 5 reconstructed with CF-DAS

(d) Microwave image of Patient 5 reconstructed with DMAS

Figure 8.8: Microwave images of Patient 5 for a range of different algorithms.
Figure 8.8: Microwave images of Patient 5 for a range of different algorithms.
Table 8.6: Summary of the analysis of Patient 5 microwave images.

<table>
<thead>
<tr>
<th>Imaging Algo.</th>
<th>ROI</th>
<th>CI-ROI present in MI?</th>
<th>SMR (dB)</th>
<th>FWHM (dB)</th>
<th>Algo. Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAS</td>
<td>CI</td>
<td>yes</td>
<td>28.20</td>
<td>17.11</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td></td>
<td>49.15</td>
<td>9.49</td>
<td></td>
</tr>
<tr>
<td>IDAS</td>
<td>CI</td>
<td>yes</td>
<td>48.65</td>
<td>8.18</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td></td>
<td>49.15</td>
<td>9.49</td>
<td></td>
</tr>
<tr>
<td>CFDAS</td>
<td>CI</td>
<td>yes</td>
<td>34.88</td>
<td>14.14</td>
<td>3</td>
</tr>
<tr>
<td>DMAS</td>
<td>CI</td>
<td>yes</td>
<td>49.37</td>
<td>10.49</td>
<td>1</td>
</tr>
<tr>
<td>CRDAS</td>
<td>CI</td>
<td>yes</td>
<td>23.61</td>
<td>20.80</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td></td>
<td>25.03</td>
<td>27.77</td>
<td></td>
</tr>
<tr>
<td>RCB</td>
<td>CI</td>
<td>no</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MI</td>
<td></td>
<td>30.72</td>
<td>12.04</td>
<td></td>
</tr>
</tbody>
</table>

indicated the presence of a fibroglandular concentration with the exception of RCB. DMAS provides the highest SMR and has been ranked first in Table 8.6.

The analysis of the microwave images produced with a variety of imaging algorithms (shown in Figure 8.2–8.8) indicate that the most algorithms demonstrate better background clutter suppression compared to DAS with the exception of RCB. The IDAS provides the highest SMR value in most cases compared to all other algorithms. However, it was noted that the responses improved by IDAS often did not correspond to the actual lesion locations (e.g., in case of Patient 1 and Patient 2). Similarly, CF-DAS also provided better clutter suppression as indicated by an improved average SMR but the location of dominant responses were found to be inconsistent with the clinical reports. Both of the algorithms improve the dominant response based on the estimated coherence of the responses. However, the coherence metrics for IDAS and CF-DAS may reward responses from
non-tumour regions within the breast.

\( \text{DMAS} \) provided the second highest average \( \text{SMR} \) value. This indicates a comparable clutter suppression to \( \text{IDAS} \) and significantly better than \( \text{DAS} \). The location of the dominant responses in \( \text{DMAS} \) images were consistent with the \( \text{DAS} \) images, as well as the actual location of lesions reported in clinical reports. In comparison to \( \text{DAS} \), \( \text{DMAS} \) improved the \( \text{SMR} \) by 44%. The improved performance of the \( \text{DMAS} \) algorithm can be attributed to its ability to virtually increase the number of measurements, while improving the coherence of responses, using pairing multiplication. Both \( \text{CR-DAS} \) and \( \text{RCB} \) performed poorly across all patients in terms of clutter suppression and particularly in terms of location of the dominant responses. \( \text{RCB} \) is known to suffer performance degradations in the presence of coherence interferences \cite{179}. Therefore, the poor performance of \( \text{RCB} \) can be attributed to the presence of multiple coherent responses and the heterogeneity of the breast. Both \( \text{CR-DAS} \) and \( \text{RCB} \) often enhanced the residual clutter from the preprocessing of the signals resulting in incorrect localisation.

### 8.4 Conclusions

In this chapter, a variety of both data independent and data adaptive algorithms for confocal microwave breast imaging have been applied to patient data. The patient data is obtained from the first patient trials conducted at the University of Calgary. The patients were scanned with the \( \text{TSAR} \) prototype for microwave imaging, as well as with X-ray mammography and \( \text{MRI} \) to aid in the interpretation of microwave images.

Results from this study indicate that the conventional \( \text{DAS} \) is able to detect most malignancies. However, a significant amount of clutter can be observed in the images produced with \( \text{DAS} \). The coherence based imaging algorithms (\( \text{IDAS} \) and \( \text{CF-DAS} \)) improve the image quality by suppressing the clutter; however they often fail to correctly localise the malignancy, particularly in case of multiple lesions and heterogeneous breasts. \( \text{CR-DAS} \) does not provide significant improvements when compared to \( \text{DAS} \). The \( \text{DA} \) algorithm \( \text{RCB} \) suffers severe performance
degradations in patients, due to the presence of coherent interferences from multiple lesions and the heterogeneity of the breast. DMAS is the only algorithm that consistently demonstrated better clutter suppression and accurate localisation capability compared to all other algorithms.
Conclusions and Discussions

In this chapter, the main conclusions and findings of the thesis are discussed. A summary of contributions is presented and future work is proposed.

9.1 Summary of main Conclusions

This thesis focused on the evaluation and development of improved signal processing algorithms for the early detection of breast cancer using radar-based microwave imaging. The two most important signal processing components of radar-based microwave imaging are the artifact removal and imaging algorithms. Firstly, a number of artifact removal algorithms were evaluated and a novel artifact removal algorithm was developed to effectively reduce the early-time artifact in monostatic as well as multistatic systems. The robustness of artifact removal algorithms to experimental noise and different scan configurations used in various experimental and clinical breast imaging prototypes was also evaluated. Further, the performance of various beamforming algorithms was evaluated using clinical patient data.

Chapter 2 presented a brief overview of the anatomy and physiology of healthy breast tissue, as well as the various types of diseases of the breast. The most recent studies of the dielectric properties of normal and cancerous breast tissues were reviewed, and microwave imaging was introduced. Furthermore, all existing
artifact removal algorithms and beamforming algorithms, as well as commonly used numerical breast phantoms and the clinical prototypes for CMI were reviewed. Comparative studies that examined the various beamforming algorithms were also considered.

Chapter 3 evaluated and compared the performance of a wide-range of existing artifact removal algorithms, along with an algorithm adapted from GPR applications. The algorithms included: Average Subtraction, Rotation Subtraction, Two adaptive filtering algorithms, Entropy-based Time-Window, Frequency-domain Pole Splitting, and Singular Value Decomposition. The algorithms were implemented and applied to MRI-based numerical breast phantoms, which were taken from the UWCEM breast phantom repository.

The results indicated that the Rotation Subtraction and Average Subtraction algorithms failed to effectively remove the early-stage artifacts, primarily due to local variations in skin thickness and differences in antenna-skin distances. Conversely, adaptive filtering algorithms performed well when applied to the portion of signal dominated by artifacts and were more robust to variations in the early-stage artifact. The Frequency Domain Pole Splitting and SVD method significantly reduced the artifact but introduced considerable distortion in the tumour response. The EBTW algorithm completely removed the part of signal estimated to contain the artifacts. However, EBTW often failed to accurately estimate the exact portion of signal containing the artifact.

Chapter 4 proposed a novel artifact removal algorithm for microwave breast imaging applications, based on the conclusions of Chapter 3. The proposed hybrid artifact removal algorithm combined the best attributes of the Wiener Filter and Entropy-based Time Window algorithms to effectively reduce the early-stage artifact while preserving the tumour response. The proposed HAR algorithm overcame the limitations of the Wiener Filter algorithm by proposing methods to estimate the artifact-dominant time-window, and by selecting an appropriate number of antennas for artifact estimation. Firstly, in HAR the EBTW algorithm was improved to
accurately estimate the artifact-dominant time-window, and the Wiener Filter algorithm was then applied over the estimated time-window to reduce the artifacts.

The HAR algorithm was applied to 3D numerical breast phantoms taken from the UWCEM repository. The results were then compared with the EBTW algorithm. Three numerical breast phantoms of varying radiographic density, were derived from MRI-based breast phantoms from the UWCEM repository and an 8 mm diameter tumour was placed at different locations within each breast phantom. Both the proposed HAR algorithm and EBTW algorithm were applied to reduce the artifacts from recorded signals and images were reconstructed with the standard DAS imaging algorithm. The results were evaluated based on performance metrics computed from both the raw signals and the reconstructed images.

The results indicated that the original EBTW algorithm underestimated the time-window and was only able to partially remove the artifact, whereas the proposed improved EBTW algorithm accurately estimated the artifact-dominant time-window. However, when the improved EBTW algorithm was used to remove the artifact, it also removed a significant portion of the tumour response signal in some channels. Therefore, in the HAR algorithm, the Wiener Filter was combined with the improved EBTW algorithm to remove the artifact. The performance metrics indicated that the HAR algorithm effectively reduced the artifacts, while preserving the tumour response.

Chapter 5 extended the HAR algorithm to the more challenging scenario of multistatic artifact removal algorithm. The HAR algorithm showed promising results when applied to monostatic signals due to the similarity of the monostatic artifact in all channels. However, multistatic signals exhibit greater variation in artifacts due to the varying propagation paths between the transmitting and receiving antennas. The multistatic artifact removal algorithm proposed a method to adaptively group the signals containing similar early-stage artifact so that each group could be separately processed through the HAR algorithm.

Multistatic signals with similar early-stage artifacts were grouped together and an entropy-based method was used to select useful signal groups that will improve
the imaging quality. The pre-selected multistatic signal groups were then separately processed through the HAR algorithm in order to remove the artifact from the multistatic signals. The MAR algorithm allowed the inclusion of multistatic signals in the imaging process, in addition to the monostatic signals. Finally, the artifact-free signals were used in beamforming to produce improved breast images. Performance metrics were computed from both the raw signals and the resultant reconstructed images. The combined monostatic and multistatic reconstructed images were compared to their monostatic equivalent based on the image quality metrics.

Results indicated that multistatic artifact removal followed by the CMM image formation process improved image quality by 50% in terms of SCR and by 23% in terms of SMR when compared to monostatic images. However, the PPRR metric computed from MAR-processed raw signals was found to be slightly poorer compared to the HAR-processed monostatic signals, as would be expected due to the greater variation in the early-stage artifacts in multistatic radar signals. The improvements in SCR and SMR indicated that residual artifacts had negligible effect on the beamformed images. Overall, the CMM algorithm, supported by the proposed artifact removal algorithm, consistently outperformed monostatic imaging across a range of test scenarios from simple homogeneous to more realistic dielectrically heterogeneous scenarios.

Chapter 6 evaluated the efficacy of the HAR algorithm in the presence of realistic antenna effects and noise from an experimental system. The robustness of the HAR algorithm to experimental noise was evaluated using both simulated and experimental breast phantoms. The numerical breast phantom and BAVA-D antenna were simulated using the FDTD method, and experimental breast phantoms were scanned with the TSAR prototype. Two experimental phantoms were used in the evaluation.

The first breast phantom had a skin layer, fatty tissue and a 16 mm diameter tumour, whereas the second breast phantom also included a 40 mm diameter glandular structure in addition to the skin layer, fatty tissue and the tumour. The skin layer, the glandular structure and the tumour were created using carbon/urethane
rubber mixtures. Different concentrations of carbon/rubber were used to mimic the
dielectric properties of skin, glandular and tumour tissues. The measurement data
was collected using the TSAR prototype. The prototype uses a single BAVA-D
antenna, which was positioned around the breast at various azimuth and elevation
angles in order to collect multiple measurements from the breast phantoms. A
numerical breast phantom, with a similar geometry to that of the experimental
breast phantom, was also created and simulated using the FDTD method.

The collected signals were processed through the HAR algorithm after some
standard preprocessing steps. The PPRR metric, which measures the ability of the
algorithm to suppress the artifact, was computed from the HAR processed time-
domains signals. The PPRR indicated that the HAR algorithm significantly reduces
the early-time artifact for both the simulated and experimental breast phantoms.
The images were produced after application of the HAR algorithm and image quality
metrics were computed from the reconstructed images. The image quality metrics
also showed the good artifact suppression capability of the HAR algorithm. Overall,
the results indicated that the HAR algorithm not only suppressed the early-stage
artifact but also reduced clutter while preserving the tumour response.

Chapter 7 evaluated the performance of two leading artifact removal algorithms
across various scan configurations used in prototypes developed for microwave
breast imaging. The algorithms considered in this study were the NSS and HAR
algorithms. Both the NSS and HAR algorithms overcome the limitations of filter-
based algorithms by proposing methods to estimate the artifact-dominant time-
window and then select appropriate neighbouring antennas for artifact estimation.
The efficacy of both algorithms was evaluated using common numerical as well
experimental breast phantoms, which were scanned using different scan patterns.
Three of the most commonly used scan patterns in microwave breast imaging
prototypes were considered in this study including: a cylindrical scan pattern, a
hemispherical scan pattern, and the adaptive/patient-specific scan pattern. The
various scan patterns considered in this study allowed for the generalisation of
results across a number of microwave breast imaging prototype systems that use a monostatic data acquisition approach.

Two numerical breast phantoms were constructed from the skin surface data acquired from patient scans. The realistic shape of both breast phantoms present realistic and challenging scenarios for the artifact removal algorithms. The third numerical breast phantom was derived from an MRI of a patient and is also representative of a realistic breast. Each breast phantom was scanned with three scan patterns. The simulations were performed using FDTD method. Two experimental breast phantoms were also used to evaluate the performance of both algorithms in the presence of realistic noise. The experimental phantoms were created from carbon/rubber mixtures. Different concentrations of carbon/rubber were used to mimic the dielectric properties of breast skin, glandular tissues and the tumour. The experimental breast phantoms were scanned with the TSAR prototype. The reflection data from each breast phantom was processed through both artifact removal algorithms after preprocessing.

In order to evaluate the efficacy of each algorithm, three signal metrics were calculated from the artifact-free signals. The metrics measured the efficacy of both algorithms to suppress the artifacts, the ability of both algorithms to suppress the late-time clutter, and the ability of both algorithms to preserve the tumour response. The artifact-free signals were then processed through an imaging algorithm to reconstruct 3D images. Finally, imaging quality metrics were computed from the reconstructed images. The signal metrics indicated that both algorithms significantly suppress artifacts, as well reduce the late-time clutter. The NSS algorithm demonstrated better artifact suppression, in addition to late-time clutter suppression. In contrast, the HAR algorithm demonstrated better tumour response preservation. In terms of imaging quality metrics, both algorithms produced similar quality images across all scan configurations and simulated phantoms. However, the HAR algorithm produced better quality images for experimental phantoms.

Chapter 8 evaluated a variety of microwave imaging algorithms using patient data. This chapter evaluated the performance of a comprehensive set of DI and DA
algorithms for the first time using clinical patient data, with non-idealised artifact removal algorithms. The patient data used in this study was obtained from the first patient study conducted at the University of Calgary. The current study selected 5 of the total 8 patients scanned in the original patient study, where clinical images either clearly identified benign or malignant lesions, or where no disease was found to be present. Two of five patients included in the study had malignant tumours, one had benign lesion and no disease was found in the remaining two patients. The patient data was first preprocessed and transformed into the time-domain. Then the patient data was processed through the NSS algorithm for early-stage artifact removal, as in the original study. Finally, the preprocessed data was used to reconstruct breast images using six different imaging algorithms. High intensity regions of interest were identified in the microwave images and objective image quality metrics including [SMR] and [FWHM] were computed for each region of interest. The presence and location of high intensity regions in the microwave images of each patient were compared with the clinically-identified regions of interests in order to evaluate the detection and background clutter suppression capability of each algorithm.

The results indicated that the images produced with a variety of imaging algorithms demonstrate better clutter suppression compared to [DAS] with the exception of [RCB]. [IDAS] provided the highest average [SMR] values, though the location of dominant responses were often found to be inconsistent with the clinical information. Similarly, [CF-DAS] also provided an improved [SMR] compared to [DAS] in most cases but the responses improved by [CF-DAS] often did not correspond to clinically identified regions of interest. The [DMAS] algorithm provided the second highest average [SMR] value, indicating a comparable clutter suppression to [IDAS] and significantly better clutter suppression than [DAS]. The location of dominant responses in [DMAS] images were consistent with the [DAS] images, as well as the actual location of lesions reported in clinical reports. The [DMAS] algorithm improved the [SMR] by 44% in comparison to [DAS]. Both [CR-DAS] and [RCB] performed poorly across all patients in terms of both the clutter suppression and the location of the dominant responses. The [DMAS] algorithm was found to be the only algorithm...
that consistently demonstrated better clutter suppression and accurate localisation capability in comparison to all other algorithms.

9.2 Future Work

The work presented in this thesis can be extended to further improve the early detection of breast cancer using CMI. The suggestions for future work in the area of CMI are presented in this section.

A novel radar-based microwave breast imaging prototype has been recently developed at the Translational Medical Device Lab (TMDLab) of National University of Ireland Galway (NUIG) [180]. Most of the prototypes reported in literature either collect data in monostatic or multistatic configuration. However, the prototype at the TMDLab has been developed with the capability to collect both monostatic and multistatic data. The HAR and MAR algorithms can be applied to both monostatic and multistatic data collected from this prototype and the advantages of CMM can be demonstrated using experimental breast phantoms and patients. The performance of the HAR algorithm in terms of tumour response preservation can be further improved by modelling and estimating the late-time clutter without the similarity assumption. Davis et al. proposed a statistical method of modelling and removing the late-time clutter [115], which can be integrated with the HAR and MAR algorithm to further improve the tumour response preservation capability of the HAR algorithm.

The patient-specific and hemispherical scan configurations provide better coupling of microwave signals into the breast and provide better imaging performance. The imaging algorithms evaluation study presented in this thesis can be extended to a large number of patients scanned with a prototype that has higher sensitivity and a patient-specific scan configuration to demonstrate the improved performance of the DMAS algorithm compared to other imaging algorithms. The work presented in this thesis provides a direction for the optimal signal processing algorithms and hardware to be used for confocal microwave imaging of the breast. The best CMI images may be obtained by combining the HAR algorithm, DMAS algorithm, and the bulk average properties estimation algorithm developed at
This combination of signal processing algorithms is expected to produce optimal results when applied to data collected from a prototype with a patient-specific/hemispherical scan configuration.

Most of the previous work in the area of CMI has been focused on the development of signal processing algorithms to improve early-stage breast cancer detection using numerical breast phantoms with dielectric properties, based on Lazebnik studies. Lazebnik studies suggested a limited contrast between the dielectric properties of healthy and cancerous breast tissues. However, recent patient studies using a number of different CMI prototypes have successfully detected tumours in a large number of patients. The evidence from patient studies indicate that a sufficient contrast for the detection of tumours using microwaves does exist. The positive results from initial patient studies motivate larger scale patient trials. Often historical patient studies were limited in terms of number of patients and patient populations recruited into the studies. For example, the clinical studies at the McGill University only recruited healthy volunteers. The patient study at the University of Calgary recruited patients with variety of breast cancers and breast densities but only 8 patients were ultimately imaged. The recent patient study at University Hospitals Bristol recruited 86 patients. The Bristol study is the most comprehensive to date, as this study included a range of pre/peri-menopausal and postmenopausal patients with varying breast densities. The study showed an overall sensitivity of 74%. However, specificity was not addressed in the study and the number of patients is still too small to draw very definite conclusions. Nevertheless, these positive results encourage larger clinical trials to evaluate the sensitivity and specificity of CMI and to accelerate the regulatory approval and clinical adoption of CMI.

Future clinical trials must be designed to include larger patient populations and must adhere to Good Clinical Practice (GCP) such that the resultant clinical data is acceptable by the regulatory authorities. In terms of future clinical prototype developments, regulations and safety standards need to be considered from the very start of the development process. For example, a system without an immersion medium would have a shorter path to clinical adoption, as it would not require
an evaluation of any potential risks to patients from the immersion medium. The current clinical prototypes have not been verified and compared using any standard phantom. Therefore, like other modalities, a realistic standard phantom and a standard evaluation criteria to evaluate the fidelity of images and signals is required for CMI. In addition, images reconstructed by each CMI prototype are displayed using different methods. Future prototypes should also adhere to the existing standardised framework for image display, three-dimensional visualisation and image presentation. The future prototypes addressing these issues, and coupled with advanced signal process algorithms as presented in this thesis, will accelerate translation of microwave imaging “from research bench to patient bedside”.

References


References


