
Translation compensation techniques and Time Window Optimisation for Inverse Synthetic Aperture Radar (ISAR) Imaging of sea vessels

Inverse Synthetic Aperture Radar



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Abstract

This dissertation covers range alignment, autofocus, and time window length optimisation for ISAR imaging of sea vessels. The rationale behind the study was to review the range alignment, autofocus, and time window length optimisation techniques found in the literature and to assess the strengths and weaknesses of the techniques. The objective was the development of an ISAR Time Window Selection Processor (ITWSP) to identify focused ISAR images in long radar recordings of sea vessels. This includes the development of a simulator to generate simulated ISAR. A lightweight processor enables efficient scanning of radar recordings to identify focused ISAR images, allowing researchers to prioritise data sets with the highest information content for further analysis without relying on resource-intensive processing. Furthermore, the study was done to determine the performance of range alignment and autofocus algorithms across different datasets.

The analysis was done by implementing the techniques on MATLAB, across different measured datasets and simulated datasets. These measured datasets came from maritime vessels, namely the Umoya Omusha vessel and the Zayaan vessel, whereas a simulator was built for the latter.

The measures used to quantify the performance of the algorithms were both qualitative and quantitative. The qualitative measure included looking for visual differences in high-range resolution (HRR) profile plots and comparing them. The quantitative measures used were image contrast and entropy.

It was found that the sub-integer envelope correlation technique performed better than the integer-shift envelope correlation technique. The best-performing technique, qualitatively and in terms of contrast, was the single reference profile envelope correlation (sub-integer shift) technique. The cumulative averaging reference profile envelope correlation technique achieved the best entropy across the measured datasets. The combination of the weighted multiple scatterer autofocus algorithm and the sub-integer range alignment technique proved to have the most favourable results. Lastly, the Optimal Coherent Processing Interval (CPI) Selection based on Image Contrast Optimisation and the Doppler Spread technique proved to be better than the Maximum Contrast Automatic time window selection technique. Selecting a combination of the best algorithms formed the ITWSP.

The alignment algorithm using sub-integer shift range alignment showed better contrast values and overall image quality compared to the integer shift range alignment algorithm, making it the clear choice for processing. For the Umoya vessel, the highest contrast value (19.5903 dB) came from the weighted multiple scatterer autofocus method, which was marginally better than the (19.5643 dB) achieved by the dominant scatterer autofocus method. On the other hand, for the Zayaan vessel, the dominant scatterer autofocus method produced a slightly higher contrast (0.0171 dB) compared to the weighted multiple scatterer method. This highlighted the fact that the choice of autofocus algorithm depends on the dataset. However, the weighted multiple scatterer autofocus method was ultimately preferred for the ITWSP due to its reliable performance across various profiles and its ability to achieve the highest contrast across both datasets. The final ITWSP, which included the envelope correlation sub-integer shift range alignment, weighted multiple scatterer autofocus, and an optimised CPI selection based on contrast and Doppler spread techniques, generated five high-quality ISAR images. From these, the best image was found for both vessels. Although the maximum contrast automatic time window selection also produced five good images, it did not deliver the single best image for either of the vessels.

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Table of Contents

Abstract	i
Acknowledgements	ii
Plagiarism declaration	iii
Table of Contents.....	iv
List of Figures	vii
List of Tables.....	x
Nomenclature.....	xi
1. Introduction.....	1
1.1 Introduction	1
1.2 Background.....	1
1.3 Problem statement	2
1.4 Objectives.....	4
1.5 Thesis contributions.....	4
1.6 Scope and limitations.....	5
1.7 Dissertation Organisation	6
2. Literature Review	7
2.1 Introduction	7
2.2 Radar Concepts.....	8
An Overview of Radar.....	8
2.2.1 Concepts Regarding Radar	8
2.2.2 Electromagnetic Waves	9
2.2.3 The electromagnetic waves' bandwidth.....	10
2.2.4 Radar configurations.....	10
2.2.5 The Range resolution.....	11
2.2.6 Pulse compression	11
2.2.7 Range concepts	11
2.2.8 The Doppler concept	11
2.3 Concepts of Radar Signal Processing.....	12
2.3.1 Introduction to Radar Signal Processing Concepts	12
2.3.2 Sampling the signal received by the radar.....	12
2.3.3 Range bins	12
2.3.4 Radar data matrix.....	12
2.3.5 Doppler Measuring.....	12
2.3.6 High-Resolution Radar	12
2.3.7 Concepts Regarding Radar Imaging.....	13
2.3.8 Synthetic Aperture Radar	13
2.3.9 Introduction to ISAR	13
2.3.10 Autofocus and Motion Compensation.....	15
2.3.11 HRR-based target classification	15
2.4 Concepts Regarding ISAR.....	15
2.4.1 Waveform Usage for HRR	17
2.4.2 Range alignment opposed to phase adjustment.....	17
2.4.3 ISAR motion compensation.....	18
2.4.4 The Effect of Coherent Processing Time Window Length (CPTWL) on ISAR images	18
2.5 Various range alignment techniques.....	18
2.5.1 The Introduction to Range Alignment Techniques	18
2.5.2 The Peak Alignment Range Alignment Technique	18

2.5.3	The Envelope Correlation Range Alignment Technique.....	18
2.5.4	Spectral-domain phase difference technique	20
2.5.5	Minimum entropy method	20
2.5.6	Sub-integer shift range alignment.....	20
2.5.7	Range Alignment with the Hough Transform	21
2.5.8	Range Alignment with the Global Method.....	22
2.5.9	Scatter-point referencing technique	22
2.6	Quality measures for the range alignment techniques	22
2.6.1	Introduction to the quality measures.....	22
2.6.2	Contrast (Sum Envelope).....	22
2.6.3	Entropy (Sum Envelope)	23
2.6.4	Global Envelope Correlation	24
2.6.5	Peak location variance	25
2.6.6	The mean squared deviation	25
2.6.7	Burst Derivative.....	25
2.7	Autofocus Methods	26
2.7.1	Autoclean Autofocus algorithm.....	26
2.7.2	Dominant Scatterer Autofocus Algorithm.....	26
2.7.3	Weighted Multiple Scatterer Autofocus algorithm.....	28
2.8	Maximum Contrast Automatic Time Window Selection (MC-ATWS).....	28
2.9	Optimal CPI Selection based on Image Contrast Optimisation and Doppler Spread.....	29
2.9.1	Range gating.....	30
2.9.2	Central instant selection.....	30
2.9.3	Optimal time window length selection.....	31
2.10	Critical Literature Survey	33
2.10.1	Strengths and weaknesses of the literature	33
2.10.2	Gaps in the literature and topics out of the scope	34
2.10.3	Link to Objectives	34
2.11	Conclusion.....	34
3.	Methodology.....	35
3.1	Introduction	35
3.2	Measured datasets.....	35
3.2.1	Umoya Omusha Vessel	36
3.2.2	Zayaan Vessel.....	37
3.3	Performance evaluation of candidate range alignment and autofocus algorithms	39
3.3.1	Integer shift range alignment algorithms.....	39
3.3.2	Sub-integer shift range alignment algorithms.....	40
3.3.3	The quality measures.....	40
3.3.4	Dataset Testing	41
3.3.5	HRR profile and bin shift plots.....	41
3.3.6	Dominant Scatterer Autofocus	41
3.3.7	Weighted multiple scatterer (Yuan) Autofocus method	41
3.3.8	Combination of the algorithms	42
3.4	Overview of the selection of the algorithms to identify effective imaging intervals.....	42
4.	Verification of translation motion compensation algorithms using Simulations.....	43
4.1	Stepped Frequency Waveforms.....	43
4.1.1	Range Resolution and Range Ambiguity in SFW	46
4.1.2	Effect of Target Velocity	47
4.2	Implementation and Results	48
4.3	Conclusion.....	61

5. Translation Motion Compensation Results	62
5.1 Range Alignment Techniques	62
5.1.1 Integer Shift (Envelope Correlation) algorithm results	64
5.1.2 Sub-integer Shift (Envelope Correlation) algorithm results	66
5.2 Combination of Range Alignment and Autofocus algorithms to find the optimal processor	69
5.2.1 Dominant Scatterer Autofocus	69
5.2.2 Weighted multiple scatterer (Yuan) algorithm	70
5.3 Conclusion of translation motion results	72
6. Optimum Image Interval Techniques Results	73
6.1 Maximum contrast-based automatic time window selection results	73
6.1.1 Umoya Omusha Vessel	73
6.1.2 Zayaan Vessel.....	78
6.2 Optimal CPI Selection based on Image Contrast optimisation and Doppler Spread.....	82
6.2.1 Umoya Omusha Vessel	82
6.2.2 Zayaan Vessel.....	91
6.2.3 Comparison of the time window algorithms and selection for the processor.....	96
6.2.4 Conclusion.....	97
7. Conclusion	98
7.1 Conclusion of the approach and objectives	98
7.2 Future work	99
7.2.1 Implementing more range alignment and autofocus techniques	99
7.2.2 Finding and implementing different quality measures	99
7.2.3 Using larger datasets with more variety	99
7.2.4 Miscellaneous	99
Appendices	103
Appendix A: Steps and derivation of the Sub-Integer algorithm	103
Appendix B: The Global Method Process	104
Appendix C: The Sum Envelope Entropy	105
Appendix D: Intra-data set performance of different range alignment algorithms	106

List of Figures

Figure 1.1 Processor with its inputs and outputs	2
Figure 2.1 Literature Review flow	7
Figure 2.2 The Radar configuration [21]	8
Figure 2.3 Radar transmission and reception [21]	9
Figure 2.4 Effect of bandwidth on range resolution [20]	10
Figure 2.5 Content of work covered [2]	13
Figure 2.6 (a) An optical image of a ship with its (b) ISAR image [26]	14
Figure 2.7 Effect of the pitch, yaw, and roll of the vessel [27]	15
Figure 2.8 a) SAR configuration to b) ISAR configuration [29]	16
Figure 2.9 Motion compensation procedure for ISAR imaging [19]	17
Figure 2.10 Effect of standard deviation on the entropy value [4]	23
Figure 2.11 Using a shifted Sinc function to highlight the influence of misalignment [4]	24
Figure 2.12 FFT image after autofocusing with Autoclean using a single dominant scatterer as reference [19]	26
Figure 2.13 Process for central instant selection [12]	30
Figure 2.14 Time Window Length Selection Process [12]	32
Figure 3.1 Experimental multimode radar deployed in Simons Town [35]	35
Figure 3.2 Image of the Umoya vessel	36
Figure 3.3 Image of the Zayaan Vessel	37
Figure 3.4 Wrapping of profiles	39
Figure 4.1 Stepped frequency waveform burst	44
Figure 4.2 Code Snippet for Simulation Set-up	48
Figure 4.3 Side-view of simulated vessel	49
Figure 4.4 Unaligned HRR profiles	49
Figure 4.5 Unfocused ISAR image with no RA	50
Figure 4.6 Flow of envelope correlation algorithm (Integer Shift) and quality measure step	51
Figure 4.7 Plot of the integer bin shifts required	52
Figure 4.8 HRR profiles after integer shift range alignment	52
Figure 4.9 Unfocused ISAR image after integer shift range alignment	53
Figure 4.10 ISAR image after Dominant Scatterer Autofocus	54
Figure 4.11 ISAR image after Weighted Multiple Scatterer Autofocus	56
Figure 4.12 Flow of envelope correlation algorithm (Sub-integer Shift) and quality measure step	57
Figure 4.13 Number of shifts required per profile	58
Figure 4.14 HRR profiles after sub-integer shift range alignment	58
Figure 4.15 Unfocused ISAR image after sub-integer shift range alignment	59
Figure 4.16 ISAR image after Dominant Scatterer Autofocus	60
Figure 4.17 ISAR image after Weighted Multiple Scatterer Autofocus	60
Figure 5.1 High-level processing steps for integer shift range alignment	62
Figure 5.2 All of the HRR Profiles for the Umoya data recording	63
Figure 5.3 All of the HRR Profiles for the Zayaan data recording	63
Figure 5.4 Subsets of the HRR profiles with the middle profile: (a)180, (b)1010, (c)1384	64
Figure 5.5 Number of shifts required per profile for middle profile: (a)180, (b)1010, (c)1384	64
Figure 5.6 Aligned range profiles (integer shift) for middle profile: (a)180, (b)1010, (c)1384	65
Figure 5.7 Unfocused ISAR image (with integer shift RA) for middle profile: (a)180, (b)1010, (c)1384	65
Figure 5.8 Subsets of the HRR profiles with the middle profile: (a)2464, (b)2970, (c)3827	65
Figure 5.9 Number of shifts required per profile for middle profile: (a)2464, (b)2970, (c)3827	65
Figure 5.10 Aligned range profiles (integer shift) for middle profile: (a)2464, (b)2970, (c)3827	66

Figure 5.11 Unfocused ISAR image (with integer shift RA) for middle profile: (a)2464, (b)2970, (c)3827...	66
Figure 5.12 High-level processing steps for sub-integer shift range alignment	66
Figure 5.13 Number of shifts required per profile for middle profile: (a)180, (b)1010, (c)1384	67
Figure 5.14 Aligned range profiles (sub-integer shift) for middle profile: (a)180, (b)1010, (c)1384.....	68
Figure 5.15 Unfocused ISAR image (with sub-integer shift RA) for middle profile: (a)180, (b)1010, (c)1384	68
Figure 5.16 Number of shifts required per profile for middle profile: (a)2464, (b)2970, (c)3827	68
Figure 5.17 Aligned range profiles (sub-integer shift) for middle profile: (a)2464, (b)2970, (c)3827.....	69
Figure 5.18 Unfocused ISAR image (with sub-integer shift RA) for middle profile: (a)2464, (b)2970, (c)3827	69
Figure 5.19 ISAR-focused image for middle profiles: (a)180, (b)1010, (c)1384 with sub-integer shift Range Alignment and Dominant Scatterer Autofocus	70
Figure 5.20 ISAR-focused image for middle profiles: (a)2464, (b)2970, (c)3827 with sub-integer shift Range Alignment and Dominant Scatterer Autofocus	70
Figure 5.21 ISAR-focused image for middle profiles: (a)180, (b)1010, (c)1384 with sub-integer shift Range Alignment and Weighted Multiple Scatterer Autofocus.....	71
Figure 5.22 ISAR-focused image for middle profiles: (a)2464, (b)2970, (c)3827 with sub-integer shift Range Alignment and Weighted Multiple Scatterer Autofocus.....	71
Figure 6.1 ISAR images after the middle profile optimisation.....	75
Figure 6.2 ISAR images after window-length optimisation.....	77
Figure 6.3 ISAR images after the middle profile optimisation.....	79
Figure 6.4 ISAR images after window-length optimisation.....	81
Figure 6.5 Spectrogram produced.....	83
Figure 6.6 Doppler spread plot.....	83
Figure 6.7 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	84
Figure 6.8 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	85
Figure 6.9 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	86
Figure 6.10 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	87
Figure 6.11 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	88
Figure 6.12 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	89
Figure 6.13 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	90
Figure 6.14 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	91
Figure 6.15 Spectrogram produced.....	92
Figure 6.16 Doppler spread plot.....	92
Figure 6.17 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	93
Figure 6.18 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	94
Figure 6.19 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	95
Figure 6.20 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast	96

Figure 7.1 ITWSP indicated by the green blocks 98

List of Tables

<i>Table 3.1 Parameters of the datasets</i>	<i>36</i>
<i>Table 3.2 Parameters of the radar</i>	<i>37</i>
<i>Table 3.3 Parameters of the datasets</i>	<i>38</i>
<i>Table 3.4 Parameters of the X-band radar.....</i>	<i>38</i>
<i>Table 3.5 Combination of algorithms.....</i>	<i>42</i>
<i>Table 4.1 Table showing the contrast and entropy values in dB.....</i>	<i>49</i>
<i>Table 4.2 Table showing the contrast value in dB</i>	<i>50</i>
<i>Table 4.3 Table showing the contrast value in dB</i>	<i>53</i>
<i>Table 4.4 Table showing the contrast value in dB</i>	<i>53</i>
<i>Table 4.5 Table showing the contrast value in dB</i>	<i>54</i>
<i>Table 4.6 Table showing the contrast value in dB</i>	<i>56</i>
<i>Table 4.7 Table showing the contrast and entropy values in dB.....</i>	<i>59</i>
<i>Table 4.8 Table showing the contrast value in dB</i>	<i>59</i>
<i>Table 4.9 Table showing the contrast value in dB</i>	<i>60</i>
<i>Table 4.10 Table showing the contrast value in dB.....</i>	<i>61</i>
<i>Table 5.1 Summary of the Contrast values obtained for both vessels</i>	<i>72</i>
<i>Table 6.1 Optimal centre profiles obtained.....</i>	<i>83</i>
<i>Table 6.2 Optimal CPTWL values for each optimal centre profile.....</i>	<i>84</i>
<i>Table 6.3 Optimal centre profiles obtained.....</i>	<i>91</i>
<i>Table 6.4 Optimal CPTWL values for each optimal centre profile</i>	<i>92</i>

Nomenclature

Acronym	Term
ADC	Analogue-to-Digital Converter
CPTWL	Coherent Processing Time Window Length
CPI	Coherent Processing Interval
DS	Doppler spread
FFT	Fast-Fourier Transform
FMCW	Frequency-Modulated Continuous Waveform
HRR	High Resolution Radar
HRR profiles	High Range Resolution profiles
IDFT	Inverse Discrete Fourier Transformation
IF	Intermediate Frequency
IFFT	Inverse Fast Fourier Transform
IFT	Inverse Fourier Transform
ISAR	Inverse Synthetic Aperture Radar
ITWSP	ISAR Time Window Selection Processor
LFM	Linear Frequency Modulated
MC-ATWS	Maximum contrast based automatic time window selection
MSA	Multiple Scatterer Algorithm
PRI	Pulse Repetition Interval
PRF	Pulse Repetition Frequency
RCS	Radar Cross-Section
RF	Radiofrequency
SAR	Synthetic Aperture Radar
SFW	Stepped Frequency Waveforms
SNR	Signal-to-Noise Ratio
T/R	Transmit/Receive

1. Introduction

1.1 Introduction

An electromagnetic image of a target can be obtained using the signal processing and imaging method known as inverse synthetic aperture radar (ISAR) [1]. Wide bandwidth pulses that bounce off a moving object are used to create an ISAR image of that target [1], [2], [3].

The technique's broad range of applications has contributed to its considerable popularity. There is a wealth of information in ISAR images that is useful for classifying objects. Aircraft, ships, and several other moving objects can be targets [4], [5]. Systems for surveillance and environmental monitoring find this especially helpful [2]. To eliminate big hotspot areas, ISAR is also used to measure the Radar Cross-Section (RCS) of platforms. The optimisation of the combination of ISAR imaging algorithms for maritime vessels is the main topic of the dissertation that follows.

Radar can aid with target classification applications [5]. Firstly, the resolution of an ISAR image is independent of the object's distance from the radar. The same does not hold true for optical sensors, which operate over a significantly shorter range. This is because the resolution in an ISAR image is solely reliant on the wavelength, bandwidth, and relative motion of the object in relation to the radar. Secondly, radar's functions and performance are not dependent on the sun or the time of day since it is an active sensor. Additionally, visual obstructions like fog, smoke, and clouds have little effect on electromagnetic waves at radar frequencies, therefore, radar image quality is not as easily influenced by the weather. Thus, in particular instances, radar can outperform optical sensors, which are reliant on weather and sunshine.

1.2 Background

In order to advance research in ISAR, measured data is essential. This involves developing algorithms that improve the focus of ISAR images and investigating techniques that utilise these images, along with High Range Resolution (HRR) profiles, for object classification.

Conducting field measurements requires careful planning, execution, and processing of large volumes of data afterwards. When processing maritime data, the number of focused ISAR images produced depends on the vessel's rotational motion. If the vessel exhibits a dominant 2-D rotational motion during certain intervals, focused images can be generated. However, environmental factors such as wind speed and swell direction affect the vessel's motion, meaning that not all recordings yield the same number of focused images with rich information for classification. Some data sets may produce numerous high-quality focused images, while others may not produce any. To address this, it is beneficial to develop a processor that can be applied to all recorded data during a measurement trial.

This processor would assess how many focused images are generated for each recording, allowing researchers to select the recordings that provide the greatest number of high-quality images for further ISAR research. In Fig. 1.1, a diagram to illustrate the inputs and outputs of such a processor is shown. Fig. 1.1 illustrates the processing workflow used to align HRR profiles. The processor takes unaligned HRR profiles as input and applies a sequence of techniques: range alignment, autofocus, and time window length optimisation. This series of steps results in the generation of an ISAR image.

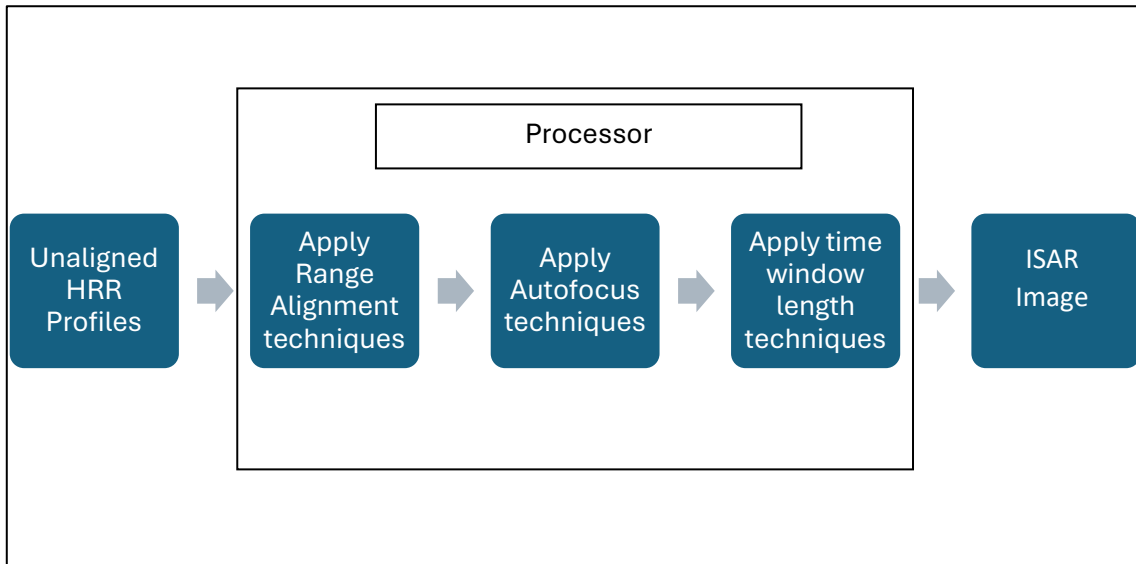


Figure 1.1 Processor with its inputs and outputs

The creation of a focused ISAR image is a result of applying two main methods to high-range resolution profiles: translational and rotational motion compensation techniques.

Range alignment and autofocus are the two primary procedures that make up translation motion compensation. Achieving sufficient range alignment is essential since an insufficient alignment would result in errors that cannot be fixed by algorithms further down the processing chain. In other words, the flaws of a poor range alignment technique cannot be fixed by the remaining processing, such as autofocus (phase correction) and polar reformatting. ISAR images would become distorted as a result [6].

The latter, rotational motion compensation, involves correcting the migration of scatterers through the range and Doppler bins due to a large change in rotation angle over the coherent processing interval (CPI). In general, this procedure is more intricate than translational motion compensation.

The performance of existing translation motion compensation and rotational motion compensation techniques has not been compared to the same measured radar data in the previous literature. In addition, there is no work done on comparing the performance of longer radar datasets of different sea vessels. The purpose of this work is to close both gaps.

1.3 Problem statement

The major challenge of the dissertation is to develop a processor to identify the number of focused ISAR images in a recording. The following needs to be overcome to achieve this:

- Robust translation motion compensation algorithms that produce focused ISAR images for measured data.
- The computational burden of translation motion compensation algorithms should be low, and iterative algorithms should be avoided.
- Identify algorithms that can automatically find focused ISAR images from a long radar recording, which are useful for classification.

The following has been done in the previous literature to solve the above challenges.

- Many translation motion compensation algorithms have been published that appear to be robust for measured data of aircraft [4], [5] and ships [4], [7]. Very little work has been done using these algorithms on many different datasets, therefore, they can have some drawbacks when attempting to use them on objects that are somewhat different. Furthermore, some of them are computationally taxing. In general, they do tend to be sufficient for classification for their respective use cases. Some of these alignment techniques include envelope correlation, peak alignment, spectral domain phase difference, Hough transforms, minimum entropy of average range profile method, sub-integer bin alignment, and the global method. For autofocus, the papers by Nel [8], Yuan [9] and Haywood [10] are considered.
- Some algorithms have been proposed to identify good imaging intervals that give rise to focused ISAR images, including the maximum contrast automatic time window selection [11], and the optimal CPI selection based on image contrast optimisation and the Doppler spread (DS) technique [12].

There has been insufficient work on addressing the problem of selecting ‘robust’ and efficient range alignment and autofocus algorithms to aid with finding focused ISAR images from a measured recording. The problem addressed in this work is the development of an ISAR Time Window Selection Processor (ITWSP) to identify the number of focused ISAR images from a long data recording.

A high-level methodology to achieve the processor is as follows:

- Identify candidate range alignment and autofocus algorithms. Algorithms should be non-iterative to reduce computational complexity.
- Evaluate the performance of range alignment and autofocus algorithms on both simulated and measured data, and select a robust and lightweight range alignment and autofocus algorithm to perform translation motion compensation in the ITWSP.
- Evaluate algorithms to identify focused ISAR images from a data recording.

By solving this problem, the advantages that are gained are that data recordings from a measurement trial can be categorised and rated according to the number of focused ISAR images in each recording. This can enable researchers to quickly identify datasets which is beneficial to the advancement of ISAR research and save them time from searching through many datasets of different quality.

The research focuses on identifying various methods of generating ISAR images of different maritime vessels and assessing the performance of these methods as well as understanding the conditions that must be satisfied for algorithms to generate a better-focused ISAR image.

The first method is translational motion compensation, where both a two-step approach as well as a single-step approach are investigated. The investigation is done using both measured data as well as simulations. The next method, namely rotational motion compensation, is also investigated using measured datasets and simulations.

Challenges arising from the compensation of translational and rotational motion need to be overcome to provide effective solutions. As previously stated, to compensate for translational motion, range alignment and autofocus are used. One such challenge is to adapt and improve existing algorithms to ensure robust performance with measured data. Another challenge is to find suitable intervals within datasets, where the vessel has a dominant 2-D rotational motion to form an ISAR image that either resembles the side view or the top view of the vessel. Not all the sections of data extracted are equal in providing meaningful information to provide good ISAR images, therefore, suitable intervals must be found. These optimum imaging intervals, which are suited to providing adequate ISAR images for the classification of both cooperative vessels and non-cooperative vessels, are discussed by Abdul Gaffar [13] and Martorella [14] respectively. Finding the CPI, an additional challenge that is investigated, is also described in the paper by Abdul Gaffar [13].

These challenges mentioned above have been addressed in the literature by Zyweck [5] and Van Rensburg [4] where effective solutions are presented. Some of the range alignment techniques discussed by Van Rensburg [4] are envelope correlation, peak alignment, spectral domain phase difference, Hough transforms, minimum entropy of the average range profile method, sub-integer bin alignment, and the global method. Furthermore, the Haywood algorithm for sub-integer shift alignment is presented in Zyweck's [5] work as well as Munoz-Ferreras [7]. To quantify the performance of these algorithms, measures such as the entropy, contrast, mean squared envelope difference, variance, and burst derivative were used. Among these, entropy and contrast are particularly popular. Entropy is valued for its sensitivity to image sharpness, with lower values indicating better focus, while contrast effectively captures the distinction between target features and background, making it useful for visual quality assessment.

In a paper by Nel [8] an autofocus algorithm, which is based on a phase gradient in the time domain, is presented. Other algorithms presented in the field include the space-variant post-filtering and the widefield polar formatting algorithm, as well as the tiered sub-aperture algorithm [15].

The single-step approach is used to overcome the limitations present in the previously discussed two-step approach. One method is the range and Doppler centroid tracking approach [16]. Another method involved optimising a quality measure, namely the burst derivative, which describes the image sharpness [17], [18]. Lastly, the Autoclean algorithm is presented in the work by Li [19].

With rotational motion, the problem is commonly solved with the formation of image reconstruction filters. This involves designing a filter where the reflections of the target are compressed into point-like responses in the image domain. Methods relating to time-frequency signal processing are used. These methods range from Range-Doppler imaging using a Fast-Fourier Transform (FFT) to Range-instantaneous-Doppler imaging, as well as back-projection and sparse reconstruction methods. Next, cross-range scaling takes place, which has methods such as correlation and optimisation based on sub-aperture images and high-order slow-time phase coefficient estimation from dominant scatterers [2].

The main gap the dissertation aims to solve is the development of the processing pipeline architecture of the ITWSP. This entails the selection of various algorithms at different stages while simultaneously evaluating these solutions on various datasets. The effectiveness of these solutions is measured using both new and pre-existing metrics. The advantages that are gained by solving the above problems are as follows. Firstly, more robust systems. Furthermore, quantitative and qualitative feedback on the performance of ISAR imaging algorithms across different datasets.

1.4 Objectives

The following are the objectives of this dissertation:

- Development of a simulator to generate simulated ISAR images of a sea vessel with 2-D motion
- Evaluate the performance of candidate range alignment and autofocus algorithms on both simulated and measured data. Thereafter, select a robust and lightweight range alignment and autofocus algorithm to perform translation motion compensation in the ITWSP.
- Evaluate the performance of algorithms to identify focused ISAR images from data recordings.

1.5 Thesis contributions

The primary objective of this dissertation was to investigate range alignment and phase correction techniques, as well as their combinations, to identify methods that yield robust alignment performance. This was

accomplished by quantifying the difference in their performance, utilising theories and methods used to assess them, specifically on a range of distinct datasets. Ultimately, the contribution is the development of an ITWSP to identify the focused ISAR images in long radar recordings of a sea vessel.

1.6 Scope and limitations

The main initiative of the dissertation is gathering measured data of objects to further the field of ISAR imaging, that is, to develop better translation motion compensation algorithms, better rotational compensation algorithms, and ISAR-based classification algorithms. The scope of the work is to take existing measured data recordings and develop a processor that can assess how many focused images are generated from each radar recording. The ones with the highest number of focused images found can be selected to aid with further research in ISAR.

This dissertation's scope was restricted to range alignment methods and phase correction techniques. In this work, eight range alignment methods, two autofocus methods, and two image interval optimisation approach algorithms were considered. The algorithms were tested and assessed on multiple datasets.

The algorithms are as follows:

- 1.1 Single Reference Profile envelope correlation Alignment (Integer shift & Sub-integer shift)
- 1.2 Adjacent Reference Profile envelope correlation Alignment (Integer shift & Sub-integer shift)
- 1.3 Non-coherent Cumulative Average Reference Profile envelope correlation Alignment (Integer shift & Sub-integer shift)
- 1.4 Sliding-Window Average Reference Profile envelope correlation Alignment (Integer shift & Sub-integer shift)
- 2.1 Dominant Scatterer Autofocus Algorithm
- 2.2 Weighted Multiple Scatterer Autofocus Algorithm
- 3.1 Maximum contrast-based automatic time window selection
- 3.2 Optimal CPI Selection based on Image Contrast optimisation and Doppler Spread

Topics outside of the scope of the work:

- Replacing the FFT with a wavelet transform
- Replacing the final FFT with super-resolution techniques like MUSIC, ESPRIT
- ISAR and compressive sensing
- ISAR and machine learning to perform classification

Furthermore, certain range alignment algorithms, such as the spectral domain phase difference and the Hough transform, are not covered in the work.

Some more limitations to the scope are as follows:

- The simulation environment is considered a 2-D rotational motion
- The measured data considered was limited to recordings of a single-mast yacht and a fishing trawler measured with an experimental X-band Pulse-Doppler Radar owned by the CSIR in Pretoria, South Africa.

1.7 Dissertation Organisation

The dissertation has the following sequential order:

Chapter 2 presents the literature review. Radar and radar signal processing principles are covered here. Along with an outline of range alignment techniques and related quality metrics, it also discusses autofocus algorithms and time window optimisation methods. It also includes a critical literature review part that examines the measured datasets.

Next, Chapter 3 discusses the methodology. Here, the software utilised and the design methodology are summarised. A step-by-step approach to how the algorithms are implemented is given.

Following, Chapter 4 presents a stepped-frequency radar simulator to generate synthetic high-range resolution profiles. Simulations are used to ensure the range alignment and autofocus techniques are implemented appropriately before testing them on observed datasets.

In Chapter 5, the translation motion compensation implementation and results are found. These are the results of the range alignment and autofocus algorithms, as well as the combination of them.

Chapter 6 presents the optimum image intervals algorithm results and implementation. The parameters set as well as the results of the two algorithms implemented are presented here.

Lastly, Chapter 7 presents the conclusion. A summary of the findings and conclusions are discussed here.

2. Literature Review

2.1 Introduction

The topics that are crucial to the research are covered in the literature review that follows. Current algorithms are discussed together with relevant theories and approaches. Additionally, important research and history are covered.

The review begins with an overview of radar principles and then moves on to the theory of radar signal processing. The review then examines essential ISAR concepts in further detail. The review then discusses several range alignment techniques that have been proposed in the literature, as well as their respective quality measures. Lastly, a critical literature review is conducted to evaluate earlier research and identify gaps in the field. Fig. 2.1 illustrates this with a basic tree diagram of the review's structure.



Figure 2.1 Literature Review flow

2.2 Radar Concepts

An Overview of Radar

The acronym for radio detection and ranging is RADAR, which is a system that measures echoes from objects. Knowing the time that a pulse was transmitted, the timing of the received echo can be converted to distance. Also, from the received echoes, if the signal is brought down to the baseband and an FFT is applied to many received echoes from the same object, the target's Doppler frequency can be estimated. Then, the Doppler frequency can be converted to the target's velocity. To do this, the systems make use of radio waves for RF radars and ultrasonic waves for ultrasonic radars. Fig. 2.2 provides a basic example of the radar process. This illustrates how an antenna converts voltages into electromagnetic waves, which are sent to the target via a transmitter. A reflected pulse, or "echo," is then reflected from the target and picked up by the antenna (via a receiver). Instrumentation radars, airborne radars, and surveillance radars are all examples of radar [20].

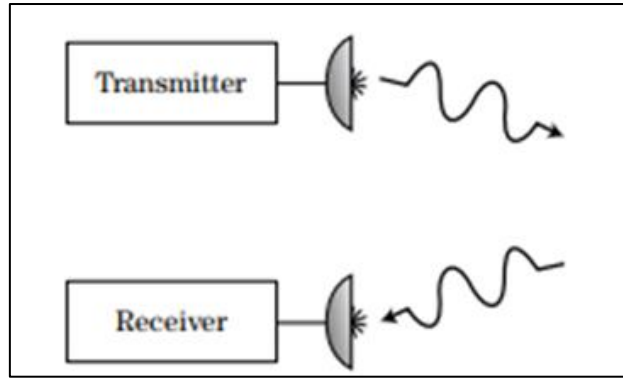


Figure 2.2 The Radar configuration [21]

2.2.1 Concepts Regarding Radar

As previously stated, a radar is a device that sends radiofrequency (RF) electromagnetic waves in the direction of a target area and receives electromagnetic waves from nearby objects. An antenna, receiver, transmitter, and signal processor are the radar's main subsystems. This is shown in Fig. 2.3 and described as follows. The electromagnetic wave is produced by the transmitter. These electromagnetic waves are captured by the antenna and transferred into a propagation medium, often air, and potentially encounter environmental conditions (e.g., precipitation). A transmit/receive (T/R) device is used to connect the transmitter and the antenna. Currents are induced on objects due to the incoming electromagnetic waves, and thereafter, RF waves are re-radiated. Unintentional echo signals from sea waves or trees are received during this process, and these signals are referred to as clutter. The echo signal, captured by the antenna, is directed through the T/R switch to a receiver protector switch that safeguards sensitive receiver components during transmission. The received signal then enters the receiver chain, beginning with a low-noise amplifier to enhance weak return signals. A mixer, driven by a local oscillator, downconverts the RF signal. Thereafter, the received RF signal is transformed into an intermediate frequency (IF) and then passed through an analogue-to-digital converter (ADC). The carriers in modulated returning signals are removed by detectors [21].

The speed of light in meters per second, c , and the time in seconds for round-trip transit, ΔT , can be used to calculate the range to a target, R . Equation 2.1 provides an expression for this [21].

$$R = \frac{c\Delta T}{2} \quad (2.1)$$

It is crucial to remember that interference might affect signals that are received. Electromagnetic interference, noise, clutter, and intentional jamming are all examples of interference.

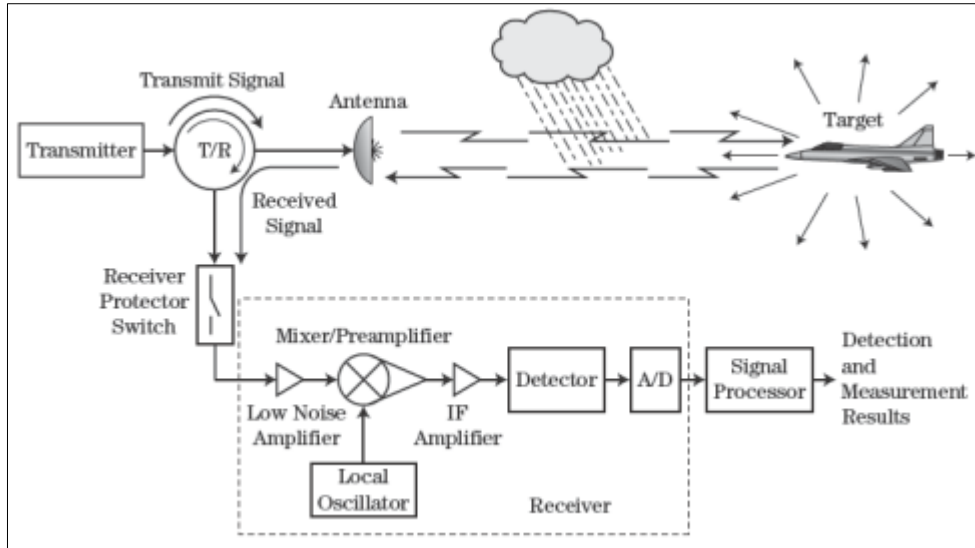


Figure 2.3 Radar transmission and reception [21]

2.2.2 Electromagnetic Waves

Electric and magnetic field waves that oscillate at a carrier frequency are known as electromagnetic waves, which are described by Maxwell's equations [21].

Wavelength, Frequency, and phase of a sinusoidal signal

A sinusoidal signal's wavelength, or λ , is the distance between any given point on a sinusoid and its initial matching point. The time interval between any given point on a sinusoid and the first corresponding point is known as the wave's period, or T . The frequency, or f , is the inverse of this. Finally, waves are distinguished by the difference in the mathematical components representing their phase [21].

Intensity and Polarisation

A wave's intensity, or Q , is its power per unit area. Furthermore, the motion and orientation of the electric field are described by the polarisation of an electromagnetic wave [21].

The Radar Equation

The signal-to-noise ratio (SNR) is a measure of a radar's target-tracking capability. It also influences detection performance. Richards et al. provide one such equation. Equation 2.2 describes this [22].

$$S/N = \frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 R^4 k T_s B_n L} \quad (2.2)$$

With:

- S/N , the SNR.
- P_t , the peak transmitter power.
- G , the transmitter gain.
- λ , the transmitter wavelength.
- σ , the radar cross-section.
- R , the distance from the radar.
- k , Boltzmann's constant

- T_s , the system noise.
- B_n , the noise bandwidth of the receiver.
- L , the total system losses.

2.2.3 The electromagnetic waves' bandwidth

The bandwidth of a waveform refers to the range of frequencies it occupies during transmission. In radar systems, this parameter is critically important because it directly determines the achievable range resolution, which is the ability to distinguish two closely spaced objects along the range dimension. This inverse relationship implies that increasing the bandwidth leads to finer range resolution, allowing the radar system to differentiate between targets that are closer together. In essence, a larger bandwidth compresses the radar pulse in time, which corresponds to a narrower range bin. Fig. 2.4 illustrates this concept [20].

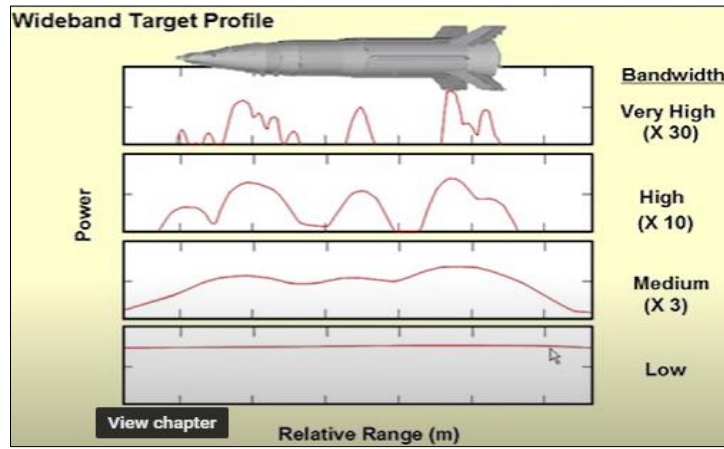


Figure 2.4 Effect of bandwidth on range resolution [20]

2.2.4 Radar configurations

Monostatic and Bistatic configurations

The monostatic and bistatic layouts are the two basic types of radar antennas. The monostatic layout's antenna serves as both a transmitter and a receiver, while the bistatic layout has separate transmitting and receiving antennas, which have a finite distance between them [21].

Continuous and pulsed waveforms

Continuous and pulsed waveforms are the two main categories of radar waveforms. For radar systems with a continuous waveform, the receiver functions while the transmitter continuously transmits a signal.

On the other hand, for radar systems that use pulsed waveforms, sequences of pulses are transmitted, and the receiver only functions when the transmitter is "off." The pulse repetition interval (PRI) is the width of the pulse plus the reception time (when the antenna is listening for echoes). The pulse repetition frequency (PRF) is the inverse of the PRI [21].

If the pulse's entire travel duration exceeds the PRI, ambiguous range measuring may occur. On the other hand, the unambiguous range measurement, R_{ua} , is the maximum range at which the range of a target can be estimated unambiguously. This is shown by Equation 2.3, where c is the speed of light [21].

$$R_{ua} = \frac{c}{2PRF} \quad (2.3)$$

2.2.5 The Range resolution

A radar system's ability to distinguish between closely spaced objects at different ranges but on the same bearing is known as range resolution, δR . This is determined by the main lobe response's width and form. As mentioned previously, bandwidth and range resolution are inversely proportional. This link is shown in Equation 2.4, which provides a formula for range resolution. Here, k is a degradation factor, B is the bandwidth, and c is the speed of light [21]. A lower δR value is referred to as enhanced resolution, and a higher δR value is referred to as reduced resolution.

$$\delta R = k \frac{c}{2B} \quad (2.4)$$

2.2.6 Pulse compression

When applied to uncompressed pulses, a matched filter derived from the transmitted waveform improves range measurement accuracy by maximising the SNR. This is achieved by correlating the received signal with the known transmitted pulse, enhancing the signal peak while spreading the noise. The filter effectively reduces the impact of noise across the waveform's bandwidth. For pulse compression waveforms, the matched filter also enables compression by aligning and processing the modulated signal, resulting in improved resolution and detection performance [21].

2.2.7 Range concepts

Waves that decouple energy and resolution through intrapulse modulation (changes in the frequency or phase within a singular pulse) or interpulse modulation (changes in the frequency or phase between consecutive pulses) are known as pulse compression waveforms. Additionally, the SNR of the output over the SNR before the filter is the pulse compression gain. Linear frequency-modulated waveforms are signals with a linear, time-varying frequency. The frequency dependence of the propagation delay through dispersive filters makes pulse compression possible. In modern-day radars, pulse compression is done digitally, by first generating a matched filter and then applying the convolution of the matched filter with the received signal at the baseband. The advantage of pulse compression is that it allows radars to employ the energy of a long pulse while achieving the resolution of a short pulse[21], [23].

2.2.8 The Doppler concept

Introducing the Doppler effect

The shift in a wave's frequency for a listener moving in relation to the wave's source is known as the Doppler effect [20]. The Doppler frequency, f_d , is the difference between the transmitted and received frequencies. For Pulse-Doppler radars, the range of Doppler frequencies that can be observed unambiguously is $[-PRF/2 + PRF/2]$. If the target's Doppler frequency is outside this range, an ambiguous Doppler frequency is observed [21].

Doppler resolution

Doppler resolution is the smallest variation in the Doppler shift of two objects with equal amplitude responses that allows for them to be reliably distinguishable. The CPI determines this. The Doppler resolution is given by $1/CPI$. A finer Doppler resolution results from a longer pulse train [21].

Multiple pulses

Radars determine a moving object's speed by utilising phase information from one pulse to the next. To estimate the target's Doppler frequency, Pulse-Doppler and frequency-modulated continuous waveform

(FMCW) radars must send out several pulses. Additionally, the necessary processing for numerous pulses is a way of coherent integration that improves the detection of objects [21].

Range-Doppler map

A visual depiction that shows Doppler frequencies on the x-axis and their associated range on the y-axis is called a range-Doppler map [21].

2.3 Concepts of Radar Signal Processing

2.3.1 *Introduction to Radar Signal Processing Concepts*

The concepts of radar signal processing are discussed here. This includes the radar concept, the effect of bandwidth and the Doppler concepts. Other topics, such as range resolution and range compression, are also discussed.

2.3.2 *Sampling the signal received by the radar*

The complex amplitudes of a pulse, $Ae^{j\theta}$, is made up of its phase, θ , and amplitude, A . The received signal is a shifted version with a new amplitude A' , assuming that it is the transmitted signal. Radar signal processing requires a coherent detector since this setup divides incoming signals into in-phase and quadrature components. Since different combinations of A' and θ yield the same output, a single channel's output is insufficient to determine both the amplitude and the phase. Moreover, the detector is unable to distinguish between phase shifts that are positive or negative [21].

2.3.3 *Range bins*

To digitise the received signal, it is sampled in discrete time intervals. Each sample corresponds to a specific range bin, representing a segment of distance along the radar's line of sight. Equation 2.5 is used to determine a range bin, which is one index of the range vector, where the sampling frequency, f_s , is equal to the bandwidth, B , to satisfy the Nyquist sampling criterion for complex-valued sampling [21].

$$range\ bin = \frac{1}{B} \quad (2.5)$$

2.3.4 *Radar data matrix*

A set of range bins is measured for each pulse when a radar sends out pulses in a CPI. A data matrix contains these matching values. The pulse number axis is referred to as "slow time" since PRF is significantly lower than the sampling rate in the range. The range is hence referred to as the "fast time" [21].

2.3.5 *Doppler Measuring*

To estimate the target's Doppler frequency, the baseband received signal undergoes pulse-Doppler signal processing. An FFT is typically applied along the slow time dimension to estimate the Doppler frequency [21].

2.3.6 *High-Resolution Radar*

Radars that function at high centre frequencies and wider bandwidths while maintaining phase stability have advanced significantly. Specifically, High-Resolution Radar is the name of the speciality group. Range resolution and angular resolution are also included in radar resolution [4], [5].

Simply put, HRR refers to radars with the ability to transmit high bandwidth signals to realise range resolution of low values, typically 1 meter or less.

2.3.7 Concepts Regarding Radar Imaging

Creating a radar image of a target that identifies its scattering centres contains rich information for target scattering. Radar images differ greatly from optical images, which require sunlight or artificial lighting to capture and record light reflected by objects. Radar images have several benefits because of their extended range, ability to work in all weather conditions, and capacity to offer the same performance during the day or the night.

In 1951, Carl Wiley mentioned that Doppler frequencies in backscattered signals from objects could be exploited for radar imaging [24]. It was thought that if a target and a radar had a relative speed, the target's components would move at various rates in relation to the antenna. The production of detailed images of target objects is made possible by precise Doppler frequency analysis using Fourier Transforms on continuous signals and discrete Fourier Transforms on sampled signals, contemporary spectrum estimation, and time-frequency renditions [25].

Synthetic Aperture Radar (SAR) and Inverse SAR, which are more favourable than non-coherent imaging methods like amplitude-only tomography, are based on this. Fig. 2.5 shows the content of the work covered in the dissertation.

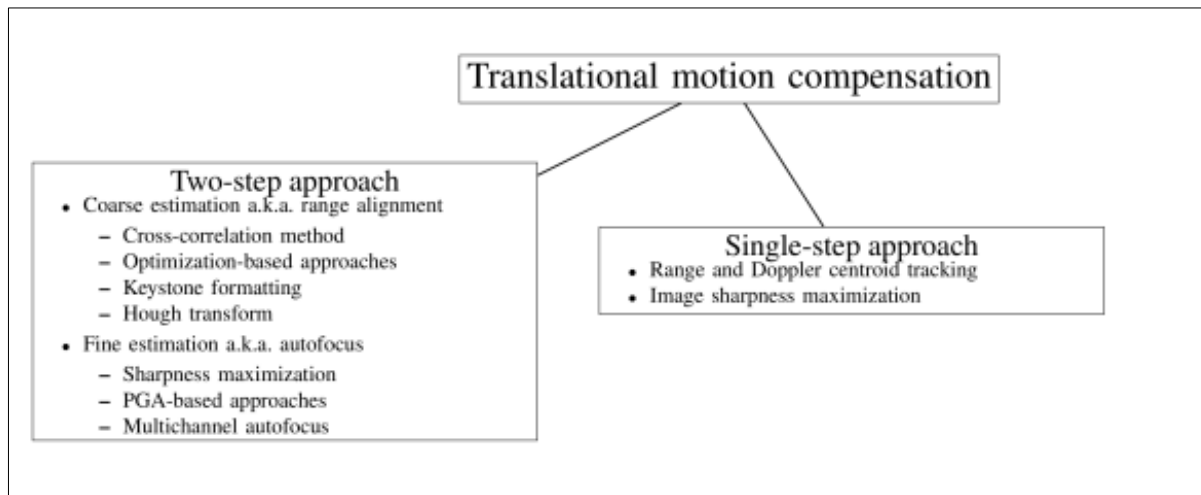


Figure 2.5 Content of work covered [2]

2.3.8 Synthetic Aperture Radar

SAR includes a radar that is fixed on a moving platform and illuminates a target's surface. A detailed SAR image is created by first acquiring data and then processing it [4]. Examples of SAR include imaging of landscapes, detection of geological structures, military reconnaissance and oceanography [24].

2.3.9 Introduction to ISAR

Although ISAR and SAR processing are similar, there are some differences. With ISAR processing, the radar remains stationary while the object is moving. The cooperativity of the object is another distinction between ISAR and SAR. In SAR, the objects are stationary objects such as the terrain, buildings, and cars. The radar platform is typically instrumented with motion sensors, and data from these sensors is used to aid with motion compensation to generate a focused SAR image. In ISAR, the motion of the target is needed to generate a meaningful image to aid with classification, and the target is typically non-cooperative. The optical and ISAR images of a ship are shown in Fig. 2.6 [26], [4].

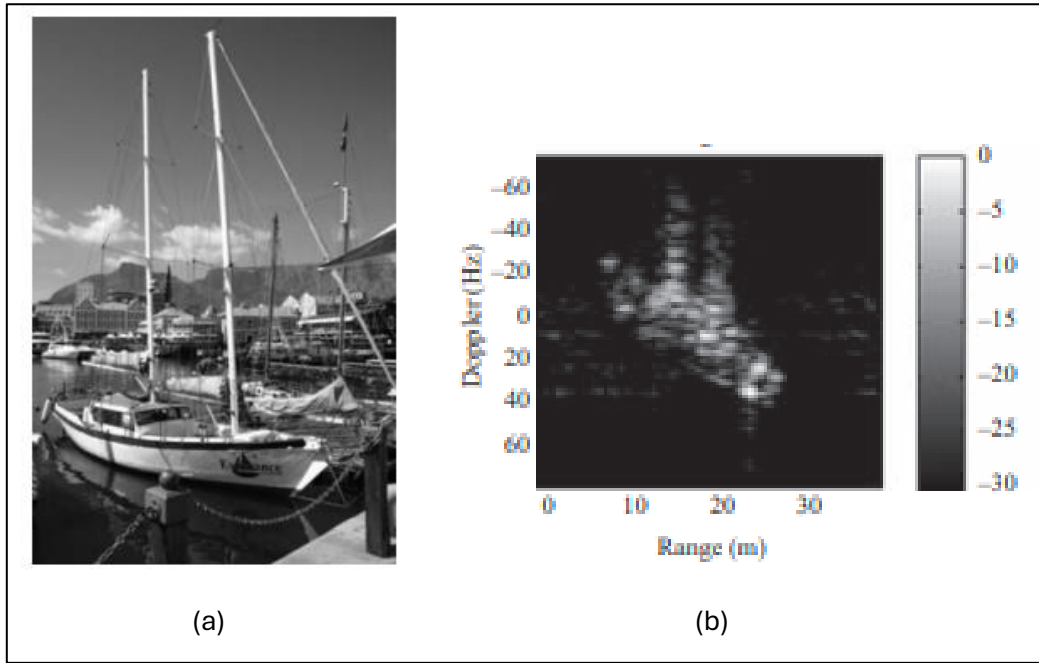


Figure 2.6 (a) An optical image of a ship with its (b) ISAR image [26]

The available information about both rotational and translational motion is used to evaluate the cooperativity. Sensors can detect rotational motion for SAR imaging. However, in ISAR, the rotational and translation motion of the target is unknown. Tracking can identify translational motion, but this blurs the ISAR image. The rotating motion cannot be concluded for objects that are not cooperative. One issue with non-cooperative objects, particularly maritime boats, is that unintended motions are produced by external factors like wave roll and pitch [4].

Radar images are created by rotating objects in relation to radars, which produce a synthetic aperture. The relative motion of the object with respect to the radar and the roll, pitch, and yaw motion, which combine to generate a rotation vector, affects the orientation of the target in the ISAR image. Chen [27] provides an illustration of this in Fig. 2.7. Fig 2.7(a) considers the scenario where a vessel is travelling inbound with respect to the radar. Consider the scenario where the vessel possesses pitch motion and negligible roll and yaw motion. In this case, the rotation motion gives rise to a side-view orientation of the vessel in the ISAR image. In Fig. 2.7(b), where the yaw motion is dominant, a top view is generated. Lastly, in Fig. 2.7(c), where roll motion is dominant, a front view is generated [4].

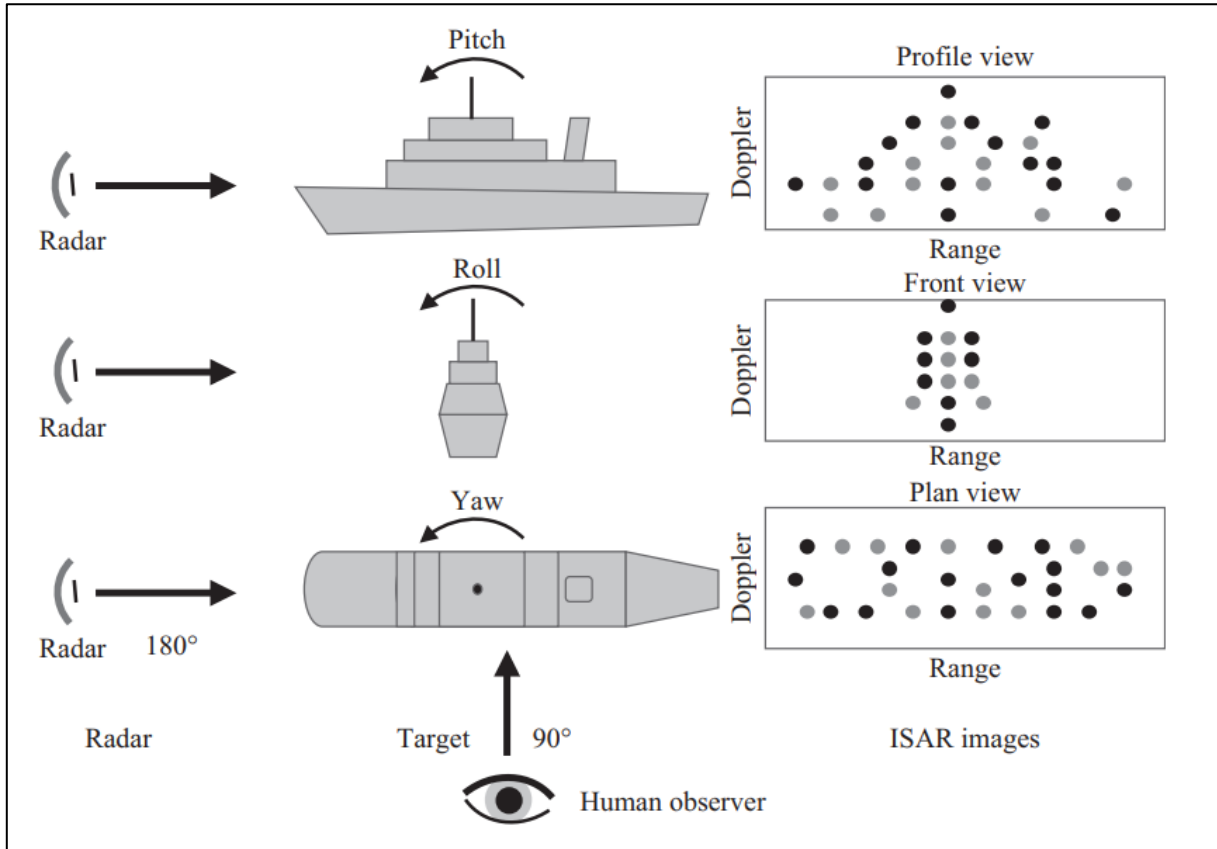


Figure 2.7 Effect of the pitch, yaw, and roll of the vessel [27]

2.3.10 Autofocus and Motion Compensation

An object's motion can be broken down into rotational motion and translational motion. The rotation motion of a vessel gives rise to ISAR images that contain rich information for classification. Motion compensation, which consists of range alignment and autofocus, is used to remove the effect of an object's translation motion. The methods are divided into two categories: parametric and non-parametric [4]. The radial motion of the target causes range profiles to be misaligned over the CPI. Consequently, range alignment and phase conjugation are the two processes that make up many non-parametric motion compensation systems [28].

2.3.11 HRR-based target classification

High-range resolution (HRR) profiles contain discriminant information about objects to assist with classification. Aligned HRR profiles are used to form an average profile with a higher SNR. For improved feature clarity, an average profile has more defined peaks and has the potential to improve classification performance compared to a single HRR profile [4].

2.4 Concepts Regarding ISAR

For a 2-D radar image to be useful for object classification, high resolution is essential in both dimensions. A wide bandwidth is needed to provide high down-range resolution, and a large antenna aperture is necessary for high cross-range resolution. Due to the practical challenges of big antennas, SAR enables a small antenna aperture to synthesise a larger aperture. The radar's ability to resolve scatterers in the cross-range dimension is referred to as cross-range resolution. The radar's down-range or slant-range dimension and the cross-range dimension are perpendicular. To go over what was previously stated, SAR operates under the premise that the target is stationary while the radar moves. On the other hand, ISAR is based on the claim that the target moves while the radar stays motionless [27].

According to one theory, the position of a target in a coordinate system affects relative motion. The reference system would be positioned on the target for SAR and on the radar for ISAR, respectively. This idea is illustrated in Fig. 2.8 [29]. By altering the reference system, a spotlight SAR configuration shown in Fig. 2.8(a) where the target is at the origin of the X-Y-Z plane, is transformed into an ISAR one in Fig. 2.8(b) where the radar now finds itself at the origin [27].

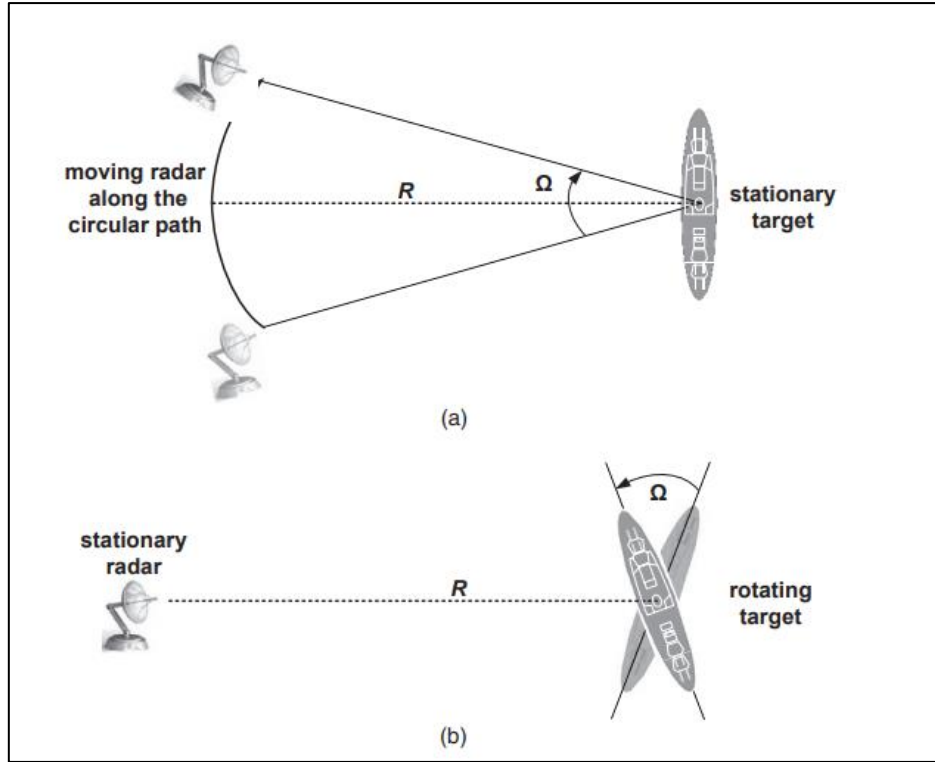


Figure 2.8 a) SAR configuration to b) ISAR configuration [29]

Fig. 2.9 illustrates the processing steps required for motion compensation. In the first step, range alignment ensures that a scatterer does not migrate through range bins over the CPI. Next, autofocus or phase correction adjusts the phase in the slow-time dimension. Both range alignment and autofocus remove the effect of an object's translational motion. For range alignment, cross-correlation is frequently utilised. The technique aligns a range profile with respect to a reference profile. Phase compensation techniques are used in the Doppler tracking [27].

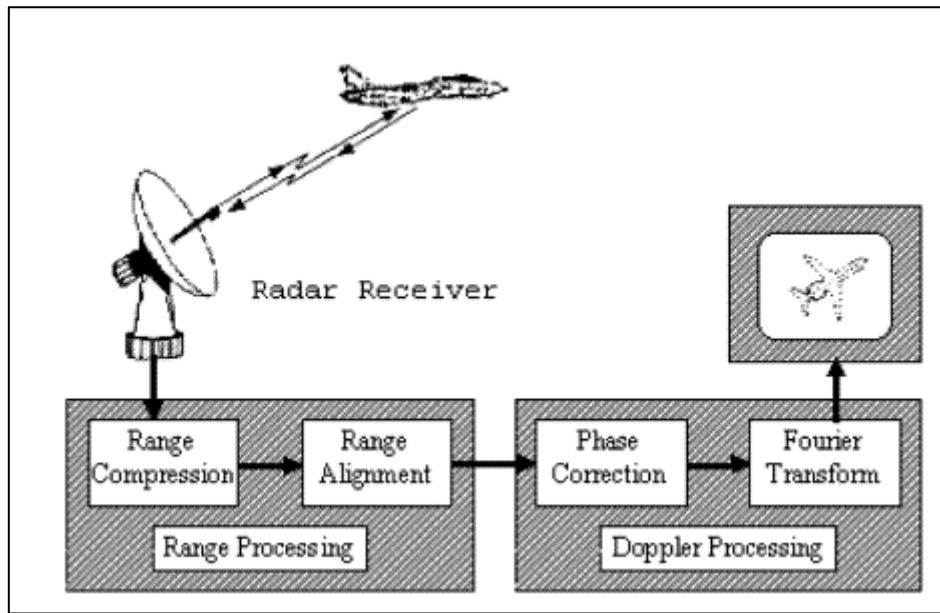


Figure 2.9 Motion compensation procedure for ISAR imaging [19]

2.4.1 Waveform Usage for HRR

Multifrequency signals or modulated continuous waveform signals should be used to attain high bandwidth. These consist of trains of modulated pulses, stepped-frequency signals, and linear frequency modulated (LFM) signals. The PRF needs to be high enough for precise Doppler frequency monitoring and to prevent Doppler anomalies [27].

LFM pulse waveform

Radars frequently use LFM waveforms, sometimes known as chirps. A single pulse with a linear variation in carrier frequency is known as an LFM pulse waveform. A windowing function, such as the Gaussian window function, determines the pulse's form [27].

FMCW waveform

Using an FMCW waveform is an alternative way to attain high bandwidth. Among them were sawtooth modulation and triangular modulation [27].

Stepped Frequency waveform

A stepped frequency waveform is defined as a series of coherent, continuous waves called pulses, where each pulse's centre frequency increases by a predetermined step of Δf . Additionally, the pulses have a defined width and are transmitted in a burst of N with a fixed PRF. A single HRR profile is obtained by applying the Inverse Fast Fourier Transform (IFFT) to the received echoes from a burst or N pulses [5], [27].

2.4.2 Range alignment opposed to phase adjustment

By aligning the range profiles, the scatterer's returned signals remain inside the same range bin, compensating for translational motion impacts from objects [27].

Phase drifts from range alignment are eliminated by a phase correction procedure called fine motion compensation, which also produces linear phase functions at bins where the target is located [27].

2.4.3 *ISAR motion compensation*

As previously stated, range alignment can be achieved using cross-correlation. This involves applying the cross-correlation operation between an unaligned profile and a reference profile. The number of range bins that an unaligned profile must be shifted to be aligned with a reference profile is ascertained using the peak and location of the cross-correlation. To complete the alignment process, the previous process is performed for each unaligned range profile. Other range alignment approaches involve the Hough transformations, minimising the entropy of an averaged range profile, and global range alignment [27].

2.4.4 *The Effect of Coherent Processing Time Window Length (CPTWL) on ISAR images*

The CPTWL value influences the ISAR images as follows. The image's resolution rises with a higher CPTWL, but the focus reduces. On the other hand, if the CPTWL drops, the image's focus rises while its resolution decreases [27].

2.5 Various range alignment techniques

2.5.1 *The Introduction to Range Alignment Techniques*

Numerous range alignment algorithms have been proposed in the literature. A limited number of techniques are analysed, and their advantages and disadvantages are highlighted in the upcoming chapter. An understanding of the range alignment techniques was gained through the in-depth comparison of range alignment techniques by Janse van Rensburg [4].

2.5.2 *The Peak Alignment Range Alignment Technique*

This technique assumes that a dominant scatterer is present throughout the CPI and serves as an alignment reference. To create aligned profiles, the algorithm identifies the peak in each unaligned profile and shifts each profile so that the peaks are aligned. The return obtained from a dominant scatterer is represented by the peak [4].

It is the most straightforward range alignment technique, and it requires minimal computational complexity to execute. This technique exhibits misalignment because of irrational assumptions. The first irrational assumption is that the data is assumed to have a single dominant scatterer, and the second is that the dominant scatterer is persistent throughout the CPI. In reality, an object may exhibit multiple dominant scatterers, and the amplitude of the dominant scatterer may fluctuate over the CPI. Thus, misalignment may result from the peak alignment process. Additionally, by limiting the range bin shifts to integer values, the dominant scatterer produces an apparent vibration. Because the target's return is positioned between two range bins, it may fold over and give the impression that it is vibrating. This issue can be alleviated by interpolating the necessary shifts to sub-integer values [4].

2.5.3 *The Envelope Correlation Range Alignment Technique*

The envelope correlation technique, which is largely used for range bin alignment, is discussed in this section. It operates by calculating the number of shifts, τ , needed to align a profile with the highest value in the cross-correlation output, denoted R_m [4].

The cross-correlation, given by X_m , which is a result of the profile being aligned, P_m , being shifted by a varying τ_m , where n is the range bin number, is calculated by Equation 2.6 [7].

$$X_m(\tau_m) = \sum_{n=1}^N R_m(n) \cdot P_m(n - \tau_m) \quad (2.6)$$

The variation of the envelope correlation technique involves the correlation of adjacent profiles, non-coherent averaging of profiles to create a reference profile, an exponentially weighted reference profile, and sliding window averaging.

Correlation of adjacent profiles

With this version, $\hat{P}_{m-1}$ replaces R_m in Equation 2.6, indicating that the reference profile is the previously aligned profile. This gives rise to Equation 2.7 [4].

$$X_m(\tau_m) = \sum_{n=1}^N \hat{P}_{m-1}(n) \cdot P_m(n - \tau_m) \quad (2.7)$$

For every profile, the cross-correlation is computed. The m profiles are aligned using the bin shift that yields the highest cross-correlation. Only integer bin shifts are considered [4].

This approach offers greater smoothness and is considered to be more accurate than peak alignment in the work in [4]. Using already aligned profiles as references is a challenge related to this technique. If an error occurs in the alignment process, then all the aligned data contains this propagating error, which is contained in the alignment vector [4].

Non-coherent averaging of profiles to create a reference profile

The reference profile used in the cross-correlation step in this technique is the non-coherent average of all the previously aligned profile envelopes[4]. Consider the scenario where m profiles were aligned. An expression for the reference profile, denoted as R_m , is defined in Equation 2.8, where m is the profile number and n is the range bin number [7].

$$R_m(n) = \frac{\sum_{i=1}^m \hat{P}_i(n)}{m} \quad (2.8)$$

Exponentially weighted reference profile

This technique has similarities to the earlier non-coherent averaging technique. But this time, an average reference profile is produced using exponential weighting. The technique is explained using a moving filter, which is provided by Equation 2.9. In the equation, W_m is the filter weight, γ_m is the filter gain, and k is the exponential factor between 0 and 1. Recall that m is the profile number.

$$W_m = k\gamma_m + (1 - k)W_{m-1} \quad (2.9)$$

To lessen the impact of earlier, aligned profiles on the chosen reference profile, varying filter weights are applied to the previously aligned profiles. The reference profile, R_m , is given by Equation 2.10.

$$R_m(n) = \frac{\sum_{i=1}^m W_i \cdot \hat{P}_i(n)}{m} \quad (2.10)$$

Sliding window averaging

The alignment can be significantly impacted by the window length of the previously measured filter due to fluctuations in the HRR profiles caused by changes in an object's aspect angle. To mitigate the impact of

fluctuation in the envelope of HRR profiles, a sliding window is used. The optimal window can be found by performing a parametric sweep [4].

Van Rensburg confirms that when compared to earlier techniques, there is a noticeable improvement in alignment performance, especially for later profiles [4]. When integer bin shifts are used, vibration degrades the alignment [4].

2.5.4 *Spectral-domain phase difference technique*

This method, described by Chen [30], relies on a few assumptions:

- A constant phase change between profiles.
- A negligible phase variation due to changes in aspect angle.
- The dominant scatterer's range bin migration is less than a single bin over successive profiles [31].

The following are the steps to put this method into practice [4]:

1. Apply the FFT to each profile.
2. Determine the phase difference for profiles that are next to one another.
3. Determine the size of the calculated phase difference's Inverse Fourier Transform (IFT).
4. The necessary range bin shift for alignment is indicated by the peak magnitude's location, which was established in step 3.

The technique works well when the assumptions are satisfied. The technique does not produce satisfactory range alignment for high-velocity targets, which results in numerous range bin adjustments for every profile [4].

2.5.5 *Minimum entropy method*

The technique is comparable to cross-correlation methods. The sole distinction is that this method's cost function is entropy, H_m , as opposed to the cross-correlation, X_m , used earlier [4]. H_m is described by Equation 2.11 [4].

$$H_m(\tau_m) = - \sum_{n=1}^N R_m(n, \tau_m) \ln R_m(n, \tau_m) \quad (2.11)$$

This technique yields fewer errors because of scintillation effects than the correlation methods, according to Xi [32]. Van Rensburg's study [4] shows a decline in alignment, especially in the profiles near the end of the data. This results from "smoothing" the reference by averaging across numerous profiles.

To include this adjustment, the previously mentioned cross-correlation-based algorithms are modified to use entropy as the cost function. The sliding window averaging method, the non-coherent averaging of the aligned profiles as a reference profile method, and the neighbouring reference profile method are some of these [4].

2.5.6 *Sub-integer shift range alignment*

In that specific study, it is suggested that the alignment method used by Munoz-Ferreras and Perez-Matinez [7] yields better range alignment than the previously discussed techniques (as well as the Global method, which is covered next). Both simulated and real data were used in the study [4].

It is evident that it is robust against target fluctuations, noise, error accumulation, and vibration impacts. The cross-correlation, $X(\tau_m)$, is calculated by using a reference profile, R_m , as described by Equation 2.12 [7].

$$R_m(n) = \frac{m}{m+1} R_{m-1}(n) + \frac{1}{m+1} P_m(n) \quad (2.12)$$

The technique involves a frequency-domain multiplication with a phase ramp to obtain sub-integer shifts. The Fourier transform's shift property produces $P_m(n - \tau_m)$, the shifted profile, described by Equation 2.13. The Fourier transform is approximated by the FFT [4].

$$P_m(n - \tau_m) = IFFT\{e^{j(\frac{2\pi}{N})\tau_m n} FFT\{P_m(n)\}\} \quad (2.13)$$

In Equation 2.13, n is a vector $[0, 1, \dots, N-1]^T$ and N is the total number of bins for each profile.

The optimal shift, $\hat{\tau}_m$, relates to the τ_m which produces the highest cross-correlation. The optimal shift is used in Equation 2.14 to create the aligned profile, $\hat{P}_m$ [4].

$$\hat{P}_m(n) = P_m(n - \hat{\tau}_m) \quad (2.14)$$

Since the permitted range bin shifts across profiles are unrestricted, claims of increased robustness in [7] are supported. But, since the algorithm might lock onto the incorrect scatterers, this could also have unfavourable results. Furthermore, it is clear from [4] that alignment deteriorates in the later profiles. This is because the reference profile's validity was weakened. When selecting or computing a reference profile to be used for alignment, it must be similar to unaligned profiles. This issue does not arise when averaging profiles. A potential method to address this is the application of a sliding window technique [4].

As described in [5], the motion compensation method proposed by Haywood [10] is an algorithm that incorporates sub-integer shifts. Three steps make up the algorithm: Doppler processing, adaptive beamforming, and radial motion compensation. The unaligned profiles are shifted by sub-integer shifts or delays by multiplying them element-wise by a phase shift vector in the frequency domain. [5] Appendix A provides a more mathematical explanation of Haywood's algorithm.

2.5.7 *Range Alignment with the Hough Transform*

A technique that makes use of feature extraction is the Hough transform. It can be used in digital image processing, image analysis, and computer vision. Finding flawed instances of objects within a class is the technique's goal. Data that is smaller than a chosen threshold of an image's peak is typically discarded to provide filtered data [4].

According to [4], compared to cross-correlation approaches, the Hough Transform methodology provides better alignment performance in a high-clutter environment. Because of this, it is well-suited for scenarios like controlling surface movement, such as objects approaching an airport terminal. Misalignments may arise because of discrepancies between a target's radial velocity and its actual velocity [4].

2.5.8 Range Alignment with the Global Method

An optimisation algorithm called the global range alignment method is used to align profiles in a way that maximises the sum envelope's contrast, or C . Equation 2.15 provides the contrast C ,

$$C = \sum_{n=0}^{N-1} S(n)^2 \quad (2.15)$$

where $S(n)$ is the sum envelope, n is the number of profiles, and N is the total number of profiles [4], [25].

For shifts applied to the present profile, the sum envelope is computed. The contrast establishes whether the range alignment is being improved or deteriorated by the iterations. An improved alignment is indicated by a better contrast, and vice versa [4].

The contrast history from each iteration is used to determine the steps. The shifts needed for range bin alignment are determined using a polynomial model. The technique's flow diagram can be found in Appendix B [4].

Compared to Wang's initial global alignment method in [25], the method in [4] has a higher computational efficiency.

2.5.9 Scatter-point referencing technique

Another technique used for ranged alignment that is worth mentioning is Scatter-point referencing [33]. Far less research has been done using this algorithm on simulated and measured data compared to the rest, due to its high computational complexity. The algorithm is left for future work.

2.6 Quality measures for the range alignment techniques

2.6.1 Introduction to the quality measures

Techniques for measuring the performance of the alignment algorithms in Chapter 2.5 are presented in this section. These performance metrics are crucial for validating the findings of the research and evaluating the quality of the work. The metrics described are as follows:

- Sum Envelope Contrast
- Sum Envelope Entropy
- Global Envelope Correlation
- The variance of the peak location
- Mean squared envelope difference
- Burst Derivative

2.6.2 Contrast (Sum Envelope)

Equation 2.16 defines the Sum envelope S , where n is the range bin number and m is the profile number. Furthermore, M is the total number of profiles, and $p(m,n)$ is denoted as the amplitude sample in the n^{th} range bin of the m^{th} range profile [25].

$$S(n) = \sum_{m=1}^M |p(m,n)| \quad (2.16)$$

The sum envelope contrast technique is the first measure that is covered. The sum envelope contrast is given by Equation 2.17 [25] different to Equation 2.15, where the starting point was $N - 1$.

$$C = \sum_{n=1}^N S(n)^2 \quad (2.17)$$

A larger contrast value is obtained by utilising a dataset with more range bins. This results in these datasets being unfairly favoured. To prevent this issue, the contrast is divided by the number of range bins [4].

Equation 2.18 is used to convert the contrast value to decibels (dB) for readability.

$$C \text{ in dB} = 10 \log_{10}(C) \quad (2.18)$$

2.6.3 Entropy (Sum Envelope)

The misalignment between the range profiles causes the entropy to be related to the standard deviation (fluctuation). Greater standard deviations suggest a decreased likelihood of identifying dominant scatterers based just on peak location. On the other hand, a lower standard deviation suggests a higher likelihood of accurately calculating the scatterers' positions [4].

Fig. 2.10 [4] shows a Sinc function with different widths to illustrate the impact of the standard deviation on the entropy value.

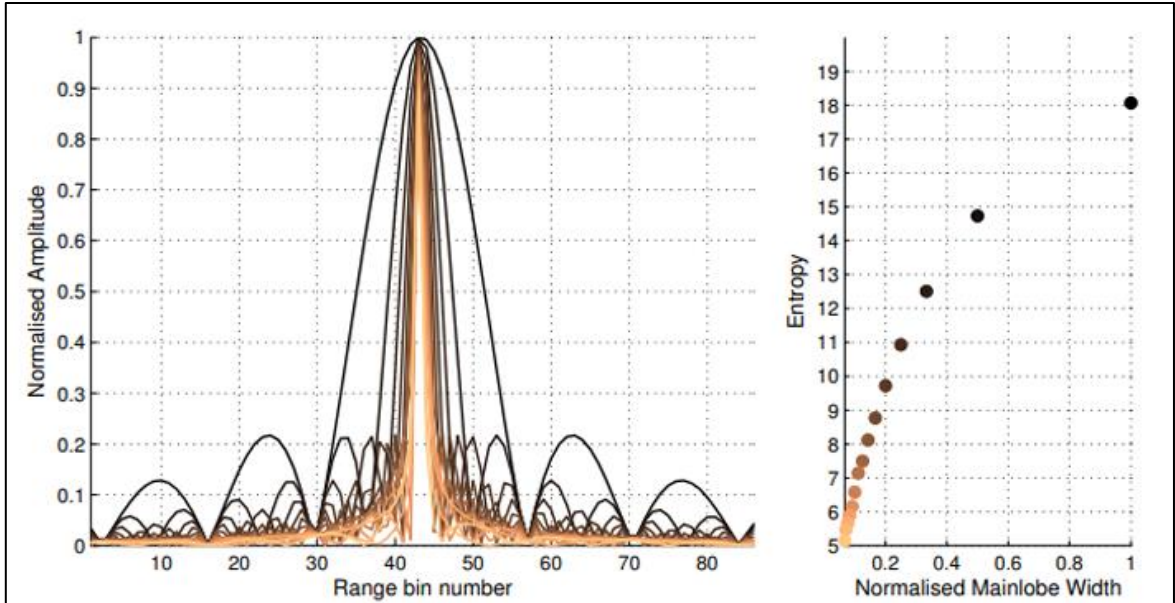


Figure 2.10 Effect of standard deviation on the entropy value [4]

The standard deviation of the average profile increases when the sum envelope is used for the computation due to profile misalignment, which increases the uncertainty of the scatterers' position. Entropy rises as a result. This idea is demonstrated in Fig. 2.11 by computing the sum envelope and entropy using a shifted copy of a Sinc function [4].

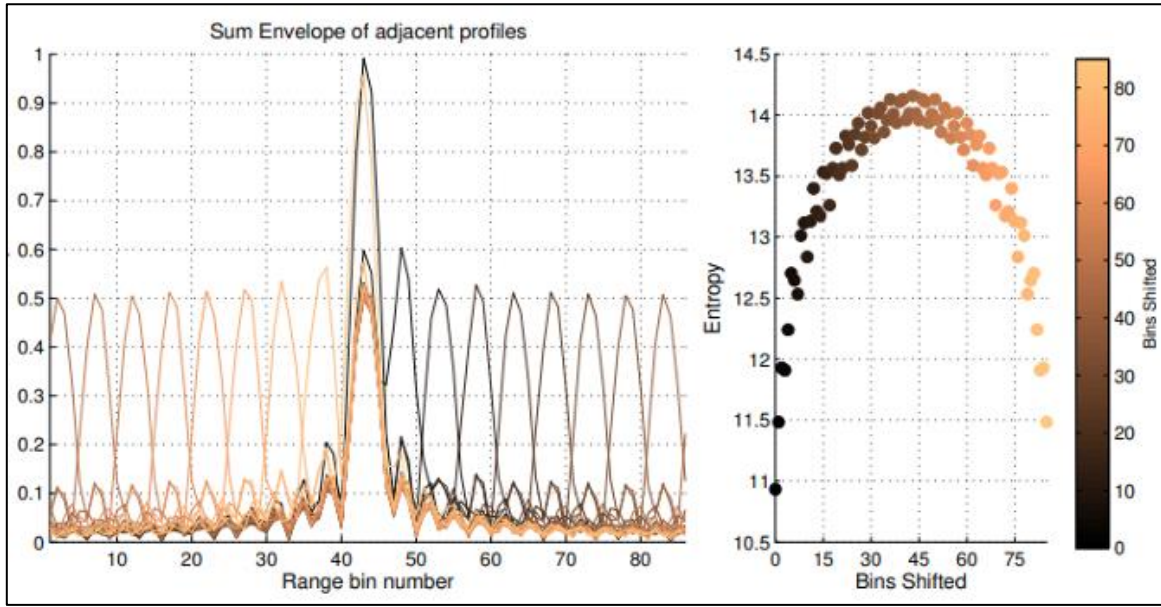


Figure 2.11 Using a shifted Sinc function to highlight the influence of misalignment [4]

Equation 2.19 is used to determine the sum entropy, or H . [4] Appendix C includes the derivation for Equation 2.19.

$$H = - \sum_{n=1}^N S(n) \ln S(n) \quad (2.19)$$

The entropy value must be divided by the number of range bins, N , just like the contrast value was in the previous section. Datasets with more range bins are not favoured due to this normalisation. [4]

The entropy in dB can be calculated by substituting H for C in Equation 2.18.

2.6.4 Global Envelope Correlation

The envelope of the correlation is a frequently used cost function for range alignment techniques. Wang [25] describes the global envelope correlation approach using Equation 2.20. In the equation, $X(m, l)$ is the envelope correlation of the profiles m and l described in Equation 2.21. $\phi(m, l)$ is a weighting function given by Equation 2.22 [4].

$$G = \sum_{m=1}^{M-1} \sum_{l=m+1}^M \phi(m, l) X(m, l) \quad (2.20)$$

$$X(m, l) = \sum_{n=1}^N |p(m, n)| |p(l, n)| \quad (2.21)$$

$$\phi(m, l) = \exp \left[- \left(\frac{l - m}{\delta} \right)^2 \right] \quad (2.22)$$

Whether δ , the spread or width of the weighting function, is fixed for the entire procedure or not is unclear in Wang [25]. According to Van Rensburg [4], it has been fixed.

2.6.5 Peak location variance

In aligned profiles, the dominating scatterers should ideally be located at the zero point. Two presumptions underlie the usage of the variance quality measure: [4]

- a) The data has one dominant scatterer that persists over the CPI.
- b) The dominant scatterer's return is always the peak return.

The approach might be characterised as the peak alignment algorithm's cost function. Equation 2.23 describes the peak location variance, $v(n_p)$ [4].

$$v[n_p(m)] = \frac{1}{M} \sum_{m=0}^{M-1} n_p(m)^2 - \left[\frac{1}{M} \sum_{m=0}^{M-1} n_p(m) \right]^2 \quad (2.23)$$

The validity of this quality measure may be negatively impacted by target fluctuation effects. It is still usable, however [4].

2.6.6 The mean squared deviation

The foundation of this metric is the idea that, in any range bin, the envelope difference between two identical profiles that are precisely aligned should be zero. The mean squared difference increases when profiles next to each other are not aligned or have different amplitudes. Equation 2.24 is used to determine the mean squared envelope difference, D [4].

$$D = \left[\sum_{n=1}^N \sum_{m=2}^M (p_{m-1,n} - p_{m,n})^2 \right]^{1/2} \quad (2.24)$$

When anomalies, such as target fluctuations, are present, the measure may yield inaccurate results. [4]

2.6.7 Burst Derivative

By using the target's reflectivity in the frequency domain to calculate the burst derivative, the IFFT needed for image contrast-based and image entropy-based autofocus is removed. Computational efficiency is increased because of this. Bocker and Jones [17] introduced the method initially, and Son [31] provided more analysis [4].

Equation 2.25 provides the burst derivative as follows: [17]

$$B(\hat{v}, \hat{a}, \hat{j}) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \left| \frac{\partial}{\partial m} \hat{P}(m, n; \hat{v}, \hat{a}, \hat{j}) \right| \quad (2.25)$$

In the equation, $\hat{P}(m, n; \hat{v}, \hat{a}, \hat{j})$ is the sample that is compensated. This is in n^{th} range bin of the m^{th} profile. The radial velocity is given by $\hat{v}$, the acceleration by $\hat{a}$ and the jerk by $\hat{j}$ [4].

2.7 Autofocus Methods

The following section describes a few autofocus algorithms proposed in the literature. In this dissertation, the dominant scatterer autofocus algorithm and the Yuan autofocus algorithm are applied to both simulated and measured data.

2.7.1 Autoclean Autofocus algorithm

Autoclean is a parametric technique built on a highly adaptable data model that accounts for arbitrary phase errors and arbitrary range migration over the synthetic aperture, which can be brought on by propagation or system instability, in addition to undesired radial motion of the target [19].

It can be classified as a Multiple Scatterer Algorithm (MSA), but it differs from other such techniques in the following ways:

1. Dominant scatterers are automatically selected in the two-dimensional domain.
2. Scatterers are not always well isolated or significantly dominant.
3. Phase and RCS information from selected scatterers are combined optimally.
4. The phase unwrapping step is not performed.

Autoclean uses a series of FFTs. It is computationally efficient and very robust according to experimental and numerical findings. A greater number of dominant scatterers for the target allows Autoclean's performance to be gradually enhanced, which is also advantageous [19].

A resulting image from [19] is displayed in Fig. 2.12. The result is for simulated data of an MIG-25 aircraft consisting of 100 ideal point scatterers. The envelope cross-correlation range alignment method was used in this case. It is evident that the algorithm performed well due to the positioning of the scatterers and clear resemblances of the iSAR image to an aircraft. The paper produced no results for maritime vessels.

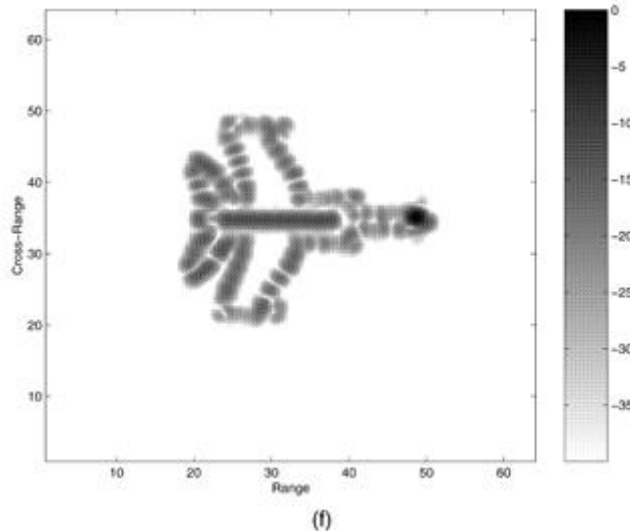


Figure 2.12 FFT image after autofocusing with Autoclean using a single dominant scatterer as reference[19]

2.7.2 Dominant Scatterer Autofocus Algorithm

As discussed, range alignment does not consider phase changes caused by the movement of targets or their instantaneous velocity. Adaptive beamforming is a technique used to correct phase distortion by compensating for geometric distortions. The method assumes the presence of a point scatterer with a large radar cross-section. Adaptive beamforming takes advantage of how range fluctuations have minimal impact

on the amplitudes of echoes from the point scatterer. Regarding signal processing, the algorithm searches for the range bin which has the lowest amplitude variance. This range bin is known as the reference range bin, and the signals received from the point scatterer here are phase-shifted to a common phase. This is known as phase conjugation [34].

The algorithm starts by measuring and storing the complex envelopes of range profiles, as shown in Equation 2.26, where l is the range bin and n , is the profile number. Next, amplitudes are corrected by dividing them by an estimate of antennas. This is given by f_n in Equation 2.27, and this step only applies to array antennas [34].

$$V_{ln}e^{j\phi_{ln}} \quad (2.26)$$

$$A_{ln}e^{j\phi_{ln}} \quad , \text{ where } A_{ln} = \left[\frac{V_{ln}}{\hat{f}_n} \right] \quad (2.27)$$

Following this, a good phase synchronising source is identified by analysing the normalised phase variance across range bins. A suitable source is one whose power is significantly higher than the average power of all range bins and exhibits the minimum phase variance. This typically indicates the presence of a dominant scatterer. The normalised variance for each range bin is calculated, and the reference range, R_o , is the range which coincides with the minimum value. This is described by Equation 2.28 [34].

$$A_{on}e^{j\phi_{on}} \quad , \text{ where } A_{on} \cong A \text{ for all } n \quad (2.28)$$

The complex envelopes of the signals received by the various profiles, from R_o , is then phase rotated, as displayed in Equation 2.29. The correct phase shift for the n^{th} profile is achieved by taking the negative value of the phase difference, described by Equation 2.30. The signal envelope of the n^{th} profile can then be simplified to Equation 2.31. Finally, phase rotation is applied to all range profiles, giving rise to Equation 2.32 [34].

$$A_{on}e^{j\phi_{oo}} \quad (2.29)$$

$$\Delta\phi_{on} = \phi_{on} - \phi_{oo} \quad (2.30)$$

$$A_{on}e^{j\phi_{on}} \cdot e^{-j(\phi_{on}-\phi_{oo})} \cong A_{on}e^{j\phi_{oo}} \quad (2.31)$$

$$A_{ln}e^{j(\phi_{ln}-\phi_{on}+\phi_{oo})} \quad (2.32)$$

It is evident why the method is referred to as the dominant scatterer algorithm, due to the rationale behind the selection of the reference range bin, which contains a dominant scatterer with minimum amplitude variation.

2.7.3 Weighted Multiple Scatterer Autofocus algorithm

In Yuan's paper [9] an ISAR ship recognition application for distortion invariant filters is presented. Small ships are analysed in the paper. A range alignment technique, namely, 'weighted correlation', along with a motion compensation technique called 'weighted multiple scatterers', make up the algorithm. Distortion-invariant filters prove useful according to the results.

The approach begins by computing the phase difference between pulses, therefore removing the need for phase unwrapping. The scatterers are chosen by calculating the mean, m , and variance, σ^2 , for each range bin. Scatterers are retained if they satisfy the criteria $\frac{\sigma^2}{\sigma^2 + m^2} < 0.16$. In the study, an average of 11 scatterers are selected (min=6 & max=18). This approach is employed because certain scatterers, despite being strong, persist only for a limited number of pulses. To address this, a distinct phase correction is applied to each compressed pulse individually. Specifically, for each selected scatterer in the first pair of range returns, the product of the complex return at pulse $n = 1$ and the complex conjugate of the return at pulse $n = 0$ is computed. This procedure is repeated for all selected scatterers across the two corresponding pulses. An estimate of the relative wave propagation noise difference can be obtained from the phase of the product of the pulse $n = 0$ and the complex conjugate of the pulse $n = 1$. To find the constant phase shift that applies to all the data in the second pulse, the values for each scatterer are averaged. This produces the phase difference $\phi_1 - \phi_0$ between the first and second pulses. This is calculated for all pulses, n , with respect to pulse $n = 0$. This provides the phase shift or difference that should be applied to each compressed pulse in relation to the initial or reference pulse. Stronger scatterers contribute more to the estimated phase term and produce better results since the amplitude of each scatterer is incorporated into the average that is computed for each pulse [9].

The algorithm gives the final pulse number versus the compressed range data. When a vertical FFT is applied to the data, the final ISAR image is produced [9].

2.8 Maximum Contrast Automatic Time Window Selection (MC-ATWS)

To create an ISAR image, a suitable selection of echoes must be processed. A time window is used as a means of this selection. The following technique involves an automatic selection of the length and position of the time window and is based on the image contrast. Image contrast is a measure of image focus, therefore, the technique involves maximising the image contrast [11].

Consider a received signal in free space in a time-frequency format, after down-conversion and I-Q signal processing, to be given by Equation 2.33. $W[f, t] = \text{rect}\left(t - \frac{\tau}{\Delta\tau}\right) \text{rect}\left(f - \frac{f_0}{B}\right)$, where rect is the rectangular function, f_0 is the carrier frequency, B is the signal bandwidth, τ is the central time instant, $\Delta\tau$ is the duration of observation, c is the speed of light in a vacuum, $R(\mathbf{x}, t)$ is the distance between the radar and some point $\mathbf{x}$ and $\zeta(\mathbf{x})$ is the target reflectivity function.

$$S_R(f, t) = W[f, t] \int \zeta(\mathbf{x}) e^{-j\left(\frac{4\pi f}{c}\right)R(t)} d\mathbf{x} \quad (2.33)$$

The Range-Doppler technique is used to reconstruct the ISAR image. This technique provides focused images when the aspect angle variation is small and when the rotation vector is constant enough. With this technique the polar grid in the frequency domain can be estimated with a rectangular grid and a 2-D FFT can be used to

create the ISAR image. The ISAR image intensity is given by Equation 2.34, where $\varphi(t)$ is the phase term necessary to achieve motion compensation and $2DFT$ is the 2-D Fourier transform [11].

$$I(\eta, \nu; \tau, \Delta\tau) = |2DFT\{S_R(f, t)\exp[j\varphi(t)]\}|^2 \quad (2.34)$$

The image contrast is defined by Equation 2.35. $A(\cdot)$ is the mean operator over (η, ν) . The IC is therefore the normalised standard deviation of the intensity of the image [11].

$$IC(\tau, \Delta\tau) = \frac{\sqrt{A\{[I(\eta, \nu; \tau, \Delta\tau) - A\{I(\eta, \nu; \tau, \Delta\tau)\}]^2\}}}{A\{I(\eta, \nu; \tau, \Delta\tau)\}} \quad (2.35)$$

The image contrast is maximised with respect to $(\tau, \Delta\tau)$ to give the optimal position and length of the time window. This gives rise to Equation 2.36 where $\Delta\tau \in [0, T_{obs}]$, $\tau \in [\Delta\tau/2, T_{obs} - \Delta\tau/2]$ and T_{obs} is the observation time [11].

$$(\tau_{opt}, \Delta\tau_{opt}) = \arg\{max_{\tau, \Delta\tau}[IC(\tau, \Delta\tau)]\} \quad (2.36)$$

The solution to the above discrete optimisation problem is as follows [11]:

1. Maximisation of the IC in relation to τ for a given guess $\Delta\tau = \Delta\tau^{(in)}$. (Let τ_{opt} be the solution)
2. Optimisation with respect to $\Delta\tau$ with $\tau = \tau_{opt}$.

2.9 Optimal CPI Selection based on Image Contrast Optimisation and Doppler Spread

The following method proposed by Martorella and Cataldo [12], aims to combine the Image contrast and Doppler spread (DS) parameters to find the optimal window length for ISAR image formation.

As discussed previously, the image contrast is a good indication of the image focus as they are directly proportional. Also, in general, a higher image contrast relates to a higher SNR. The IC may sharply rise, though, if one prominent peak were to dominate an unfocused ISAR image. Furthermore, the IC may cause an artificial increase for frames that contain certain sweeps if the energy of the HRR profile happens to increase for those sweeps or if the receiver's ADC happens to saturate. In the above cases, simply using the image contrast parameter would result in the algorithm producing unfavourable results. To overcome this, the Doppler spread information is used in conjunction with the image contrast [12].

The scatterer's radial speed in relation to the radar's antenna determines the Doppler shift that the scattering source introduces. The difference between the highest and lowest Doppler shifts that each scattering source on the target of the observation introduces is known as the Doppler spread. In the range-Doppler domain, a large Doppler spread suggests that the radial speeds of various scattering sources differ significantly, making them easily discernible. The output ISAR image is typically used to estimate the Doppler spread for non-cooperative objects. It can also be estimated by examining the spectrogram of the received signal [12].

The high-level method of the Optimal CPI Selection based on Image Contrast Optimisation and Doppler Spread algorithm is described in [12] as follows:

1. Select an appropriate time window length manually T_0 ;
2. Establish the optimal central instant $\hat{t}_{opt}$ for the CPI length T_0 ;
3. Establish the optimal time window length $\hat{T}_{opt}$ centered on $\hat{t}_{opt}$.

2.9.1 Range gating

The "alignment and cut" stage comes before the suggested CPI selection process. This is necessary because to estimate the target's Doppler spread index, the time-frequency spectrum of the received signal is required. To reduce the impact of Doppler centroid variation on the spectrogram, the HRR profiles are aligned. Using consecutive range gating is also useful for producing a cleaner spectrogram with less noise. In the paper by Martorella and Cataldo [12], the chosen radial motion compensation algorithm incorporates a third-order model for the radar-target distance, which accounts for variations in the target's velocity. If the acceleration component of the target is corrected sufficiently, the only fluctuation in the spectrogram along the slow-time axis comes from the Doppler spread variation. Compensation of the radial velocity of the target allows for unnecessary cells, which are not occupied by the target, to be removed, as well as the removal of noise(clutter) samples.

2.9.2 Central instant selection

The first step is to define an initial time length, T_0 , which is a plausible guess for a specific application. The second step is then to determine the optimal CPI central instant $\hat{t}_{opt} \in [\frac{T_0}{2}, T_{Tot} - \frac{T_0}{2}]$, where the total observed time is given by T_{Tot} . Fig. 2.13 gives an overview of the central instant selection procedure. The first step calculates the time-frequency spectrogram of the aligned HRR profiles using time windows of T_0 seconds. T_0 does not need to be optimal, but just sufficient to produce the spectrogram [12].

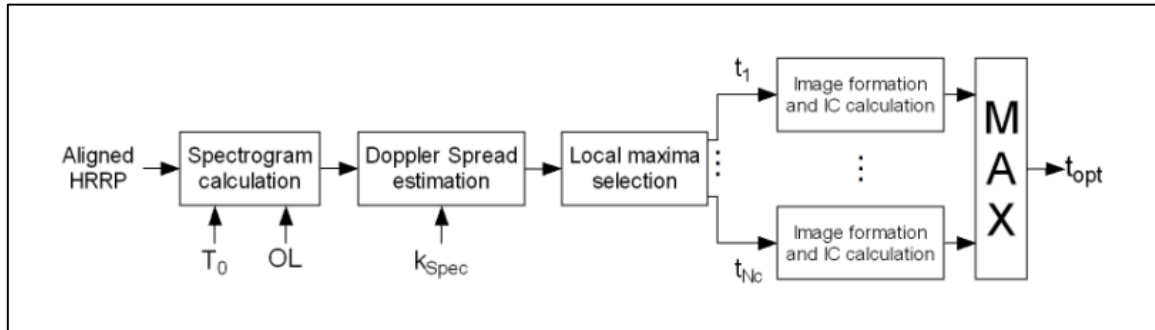


Figure 2.13 Process for central instant selection [12]

The spectrogram $S(v, t)$ is a $[N_{fft} \times N]$ matrix in the slow-time domain. Each column represents an approximation of the frequency content of the input HRR profiles. Mathematically, it is given by Equation 2.37.

$$S = [s_1, s_2, \dots, s_N] \in \mathbb{C}^{N_{fft} \times N} \quad (2.37)$$

where each column vector, s_i , for $t \in [(i-1)(T_0 - OL), iT_0 - (i-1)OL]$ and $i \in [1, 2, \dots, N]$ where $N = [(T_{Tot} - OL)/(T_0 - OL)]$, is given by Equation 2.38. The delay-time dimension is given by τ .

$$s_i = \mathcal{F}T_{t \rightarrow v} \left\{ \sum_{\tau} HRRP(\tau, t) \right\} \in \mathbb{C}^{N_{Nfft} \times N} \quad (2.38)$$

In Equation 2.38 the aligned HRR profiles are segmented into T_0 second intervals within $OL < T_0$ seconds overlap. The Fourier transform (in the slow-time domain) is applied to the sum of the result. This way, the column vectors, s_i , of N_{Nfft} elements, are obtained. v is the Doppler variable given in Hz. The i^{th} column of S is the Spectrogram within a time window of T_0 seconds and centred on Equation 2.39 [12].

$$t_i = \left(i - \frac{1}{2}\right) T_0 - (i - 1) OL \quad \text{for } i \in [1, 2, \dots, N] \quad (2.39)$$

Based on the result of the spectrogram, the DS trend is estimated. A threshold, λ_i , is set for each column of s_i , where $\lambda_i = \mu_i + k_{spec} \cdot \sigma_i$. μ_i is the mean and σ_i is the standard deviation. k_{spec} is a manually set variable based on the application. The DS for the i^{th} column is then given by Equation 2.40, where Δf is the Doppler frequency spacing. By selecting the DS maxima exceeding a certain threshold (e.g. the mean), a vector of N_c central candidates are formed. For each N_c , an ISAR image is formed by using the same amount of time windows, centred on every central instant candidate. The ‘best’ central instant candidate, $\hat{t}_{opt}$, is given by the ISAR image which maximises the image contrast. The image contrast is calculated by dividing the image standard deviation by the image mean [12].

$$DS(i) = \sum_v [S(v, t_i) > \lambda_i] \Delta f \quad (2.40)$$

2.9.3 Optimal time window length selection

Adopting the greatest image contrast criteria while keeping the image's Doppler occupancy largely constant is the optimal window length selection technique. The idea is to ensure that the target's Doppler occupation remains steady as the CPI rises, while the image's cross-range resolution falls. An illustration of the algorithm is depicted in Fig. 2.14 [12].

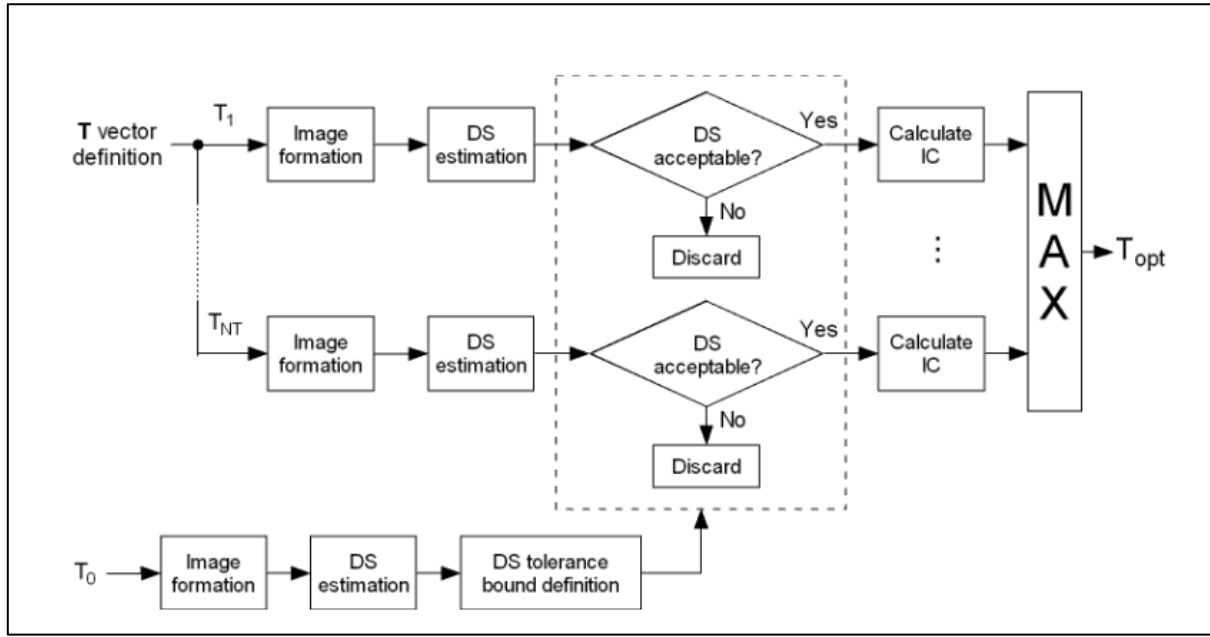


Figure 2.14 Time Window Length Selection Process [12]

The first step is to define a DS tolerance bound, which is seen in Equation 2.41. The Doppler occupation, $DS(\hat{t}_{opt}, T_0)$ for the central instant $\hat{t}_{opt}$, and Time length, T_0 , is estimated from the ISAR image formed. k_{DS} is a parameter that is set depending on the scenario. Next, $T = [T_1, T_2, \dots, T_i, \dots, T_{N_T}]$ of N_T CPI duration candidates are defined. The ISAR image is then formed for each $DS(\hat{t}_{opt}, T_i)$, and the Doppler occupation is estimated. If the Doppler spread falls within the tolerance band, the image contrast is calculated, otherwise, that window length candidate is discarded. The CPI candidate length which maximises the image contrast is chosen [12].

$$DS(\hat{t}_{opt}, T_0) \pm k_{DS} DS(\hat{t}_{opt}, T_0) \quad (2.41)$$

The DS estimation task begins by summing the ISAR image (dB) in the delay-time (range) direction. This is given mathematically by Equation 2.42, where $I(\tau, v)$ is the ISAR image formed and $\sum_I(v)$ is the Doppler profile. To estimate the DS of the image and the optimal threshold for $\sum_I(v)$ is automatically set [12].

$$\sum_I(v) \doteq \sum_{\tau} [20 \log_{10} |I(\tau, v)|] \quad (2.42)$$

A collection of threshold candidates is defined, and the number of Doppler bins for which each candidate's $\sum_I(v)$ exceeds is determined. A DS curve is calculated, shown mathematically by Equation 2.43, where Δv is the Doppler spacing (Hz). λ_{DS} represents the threshold candidate. The optimal threshold is obtained from the $DS(\hat{t}_{opt}, T_i, \lambda_{DS})$ curve by approximating it with the hyperbolic formula in Equation 2.44 [12].

$$DS(\hat{t}_{opt}, T_i, \lambda_{DS}) = \sum_{v: \sum_I(v) > \lambda_{DS}} \left(\sum_I(v) \cdot \Delta v \right) \quad (2.43)$$

$$y = \frac{1}{ax + b} + c \quad (2.44)$$

x and y are defined by Equation 2.45 where λ_{DS} and $DS(\hat{t}_{opt}, T_i, \lambda_{DS})$ is normalised between the values of 0 and 1. Using a least mean squared error method, the parameters a, b, c are estimated. This gives rise to equation 2.46, where N_λ is the number of threshold candidates [12].

$$x \doteq \frac{\lambda_{DS} - \min(\sum_I(v))}{\max(\sum_I(v)) - \min(\sum_I(v))} \text{ and } y \doteq \frac{DS(\hat{t}_{opt}, T_i, \lambda_{DS})}{DS(\hat{t}_{opt}, T_i, \lambda_{DS} = \min(\sum_I(v)))} \quad (2.45)$$

$$(\hat{a}, \hat{b}, \hat{c}) = \arg \min_{a,b,c} \left\{ \frac{1}{N_\lambda} \sum_{\lambda_{DS}} \left[y - \left(\frac{1}{ax + b} + c \right) \right]^2 \right\} \quad (2.46)$$

When the parameters $\hat{a}, \hat{b}, \hat{c}$ are estimated, the optimal threshold is created by taking the vertex of the hyperbola, given by $x_v \doteq \frac{\sqrt{\hat{a}-\hat{b}}}{\hat{a}}$. Thus, from Equation 2.45 the optimum threshold is given by Equation 2.47. The final DS measure of the image is given by Equation 2.48 [12].

$$\lambda_{DS,opt} = \min \left(\sum_I(v) \right) + x_v \cdot \left(\max \left(\sum_I(v) \right) - \min \left(\sum_I(v) \right) \right) \quad (2.47)$$

$$DS(\hat{t}_{opt}, T_i) = \sum_{v: \sum_I(v) > \lambda_{DS,opt}} \left(\sum_I(v) \cdot \Delta v \right) \quad [Hz] \quad (2.48)$$

2.10 Critical Literature Survey

2.10.1 Strengths and weaknesses of the literature

The ideas of radar and its processing were discussed in this chapter. This information is necessary to understand the dissertation's specific goal, which relates to the development of a lightweight processor to identify the number of focused ISAR images in a radar recording.

Additionally, a sufficient number of range alignment techniques have been published in the literature and summarised by Janse Van Rensburg [4]. Both the algorithms' derivations and functionality are explicitly examined. Additionally, these algorithms' advantages and disadvantages are succinct and apparent.

The measures of alignment are also explained. Both Wang's [25] and Van Rensburg's [4] work provides a detailed explanation of the range alignment quality measuring algorithms.

Two detailed autofocus algorithms are presented by Yuan [9] and Li et al. [19].

A lack of clearly explained processing steps to demonstrate how the algorithms and quality measures were applied to guarantee the validity of the findings provided is one of the literature's weaknesses. This is particularly evident in the work by Zyweck [5] and Van Rensburg [4].

2.10.2 Gaps in the literature and topics out of the scope

The problem of selecting a reliable and efficient range alignment and autofocus method for identifying focused ISAR images from recorded data has not been given enough attention in the literature. To address this, this dissertation introduces an ITWSP designed to determine the number of focused ISAR images from a large dataset.

2.10.3 Link to Objectives

The dissertation can continue by demonstrating the use of some of the range alignment algorithms found in the studied literature using measured and simulated datasets. This required the development of a simulator to generate ISR images of maritime vessels having 2-D motion, as well as gathering measured data.

The algorithms' performance was compared after they were applied to various datasets, as well as the simulated data. A best performance criterion was created to assess performance using contrast and entropy values, as these metrics were applied to measured data of sea vessels and were effective in [12] and [26]. Next, the autofocus techniques, namely dominant scatterer autofocus and weighted multiple scatterer autofocus, were used. A combination of range alignment and autofocus techniques was tested to find the best combination for the formation of an ITWSP.

2.11 Conclusion

Important concepts that are crucial to ISAR were covered in the literature review. Current algorithms in the literature and relevant theories are discussed. Research on the subjects was also examined. Radar theory concepts, ISAR concepts, radar signal processing concepts, range alignment procedures, autofocus techniques, and quality measurement techniques were among the subjects covered. A significant gap in the literature is the lack of selecting a suitable combination of range alignment and autofocus algorithms which is both robust and specific to maritime vessels. The dissertation aims to fill this gap.

3. Methodology

3.1 Introduction

This chapter outlines the methodology used to develop an ITWSP to determine the number of focused ISAR images in a data recording. Identifying data recordings with many focused ISAR images is beneficial for ISAR research, such as the development of robust translation motion compensation techniques, rotational motion compensation techniques, cross-range scaling, and ISAR-based classification techniques. The approach discussed in this chapter includes measured data used in this study, a study of low complexity translation motion compensation techniques, performance evaluation of candidate translation motion compensation algorithms to select the best range alignment and autofocus algorithms, and a comparison of the most effective algorithms to identify effective imaging intervals that produce ISAR images useful for classification.

Firstly, the measured data used in the work is described. After that, the range alignment algorithms used in the dissertation are listed. The quality metrics that were employed are then listed. The range algorithms' testing on various data blocks is the subject of the discussion that follows. Additionally, a description of the plots used in the study is provided. The penultimate discussion relates to the autofocus algorithms and the method of combining algorithms to find the best overall processor. Lastly, the two single-step algorithms are discussed.

3.2 Measured datasets

The research was done on two datasets provided by the Council for Scientific and Industrial Research (CSIR). The maritime vessels are namely the Umoya Omusha vessel and the Zayaan vessel. For each vessel, 3 datasets are respectively used, with the dataset providing the most accurate results being presented and analysed. The parameters and details of the datasets are discussed below.

An X-band experimental pulse-Doppler tracking radar was used to generate high-range resolution profiles of vessels, achieving a range resolution of better than 1 meter. The radar employs stepped frequency waveforms (SFW) to generate these profiles and employs mono-pulse tracking with a pencil-beam antenna radiation pattern in the sum channel. One of its key strengths is the full programmability of several radar waveform parameters, including PRI, pulse code, and the number of pulses in a burst. For SFW, a burst of pulses is used to generate a single HRR profile, enhancing the radar's capability in high-resolution target tracking.



Figure 3.1 Experimental multimode radar deployed in Simons Town [35]

Several measurements of sea vessels were taken in Simons Town, Cape Town, during September and October 2010. Fig. 3.1. depicts the radar. In this work, data recordings from two sea vessels are used: a single-mast

yacht and a fishing trawler. The single-mast yacht was called the Umoya Omusha and the fishing trawler was called the Zayaan.

3.2.1 *Umoya Omusha Vessel*

An image of the vessel is displayed in Fig. 3.2. The length of the boat was 12.5 m with a width of 3 m. It features a mast of approximately 20 m in height. All of the 3 datasets used contain 1789 profiles, and each profile had 86 range bins. The parameters of the 3 datasets used are given in Table 3.1. The parameters of the radar are given in Table 3.2.



Figure 3.2 Image of the Umoya vessel

Table 3.1 Parameters of the datasets

Datasets	Alias	Profiles	Range bins
DAP_2010-10-06_18-00-05_002_Umoya_P872_55212.	Umoya 1A	1789	86
DAP_2010-10-06_18-01-54_002_Umoya_P873_50446.	Umoya 1B	1789	86
DAP_2010-10-06_18-14-21_002_Umoya_P872_55336.	Umoya 1C	1789	86

Table 3.2 Parameters of the radar

Parameter	Value
Central frequency (f_0)	~ 8.5 GHz
Bandwidth (∇f)	8 MHz
PRF	75 Hz

It is critical to select a suitable data length for analysis for the initial range alignment algorithms. This is carried out as follows, with the CPI selected to be roughly 0.5 seconds.

$$\begin{aligned} \text{Length of profiles} &= \text{PRF} * \text{CPI} \\ \text{Length of profiles} &= 75\text{Hz} * 0.5\text{s} \\ \text{Length of profiles} &= 37.5 \end{aligned}$$

To make the profile length a factor of two the following operation is done:

$$\begin{aligned} 2^x &= 37.5 \\ x &= 5.23 \text{ (nearest integer is 5)} \\ \text{Length of profiles} &= 2^5 = 32 \text{ (closest power of 2)} \end{aligned}$$

3.2.2 Zayaan Vessel

The marine vessel, referred to as Zayaan, is illustrated in Fig. 3.3. The same dataset acquired from this ship was previously utilised by Abdul Gaffar et al. in [35]. The commercial fishing boat features a mast that is [3.5 m 7 m] high and measures 9 m in length and 3 m in breadth. The parameters of the 3 datasets used are given in Table 3.3 [35].



Figure 3.3 Image of the Zayaan Vessel

Table 3.3 Parameters of the datasets

Datasets	Alias	Profiles	Range bins
DAP_2010-10-14_09-43- 33_010_zayaan_inbound_singlebin_P455_G1_sb_HRR	Zayaan 2A	4473	96
DAP_2010-10-14_09-42- 18_010_zayaan_out_singlebin_463__P463_T001	Zayaan 2B	8953	48
DAP_2010-10-14_18-59- 55_014_Zayaan_P870_G1_sb_HRR	Zayaan 2C	2901	69

An experimental X-band Pulse-Doppler radar was used to collect the vessel's data. Table 3.4 displays the radar's parameters. High-range resolution profiles (HRR profiles) were obtained using SFWs. [35]

Table 3.4 Parameters of the X-band radar

Parameter	Value
Central frequency (f_0)	~ 10 GHz
Bandwidth (∇f)	10 MHz
PRF	175 Hz

As before a suitable data length for analysis for the initial range alignment algorithms needs to be selected.

$$\begin{aligned}
 \text{Length of profiles} &= \text{PRF} * \text{CPI} \\
 \text{Length of profiles} &= 175\text{Hz} * 0.5s \\
 \text{Length of profiles} &= 87.5
 \end{aligned}$$

To make the profile length a factor of two the following operation is done:

$$\begin{aligned}
 2^x &= 87.5 \\
 x &= 6.45 \text{ (nearest integer is 6)} \\
 \text{Length of profiles} &= 2^6 = 64 \text{ (closest power of 2)}
 \end{aligned}$$

The results of the algorithms are influenced by the interval in which this length of profiles is used. This is because some profile blocks are superior to others. Additionally, certain profile blocks clearly show profile wrapping. The interval [900 964] is selected in Fig. 3.4 to illustrate this.

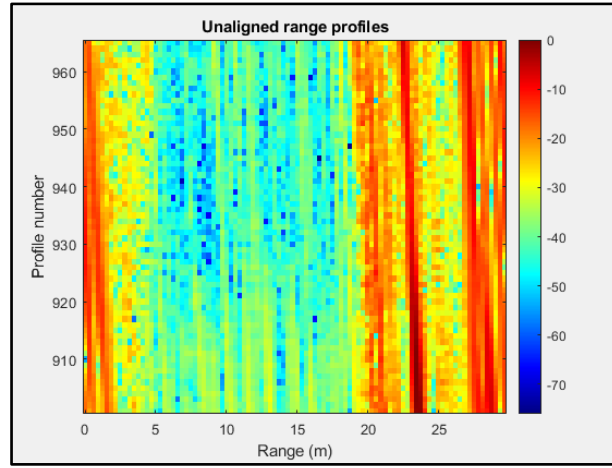


Figure 3.4 Wrapping of profiles

3.3 Performance evaluation of candidate range alignment and autofocus algorithms

There are many range alignment and autofocus algorithms in the literature. Some are iterative and others are non-iterative. Iterative ones are more computationally expensive. In this work, several low-computational complexity candidate range alignment and autofocus algorithms are identified, and their performance was compared using both simulated and measured data. The performance metrics used to quantify the performance of the algorithms are the contrast and the entropy values of the ISAR image. The best-performing candidate range alignment algorithm and autofocus were chosen to perform translation motion compensation in the ITWSP to determine the number of focused ISAR images in a data recording.

3.3.1 Integer shift range alignment algorithms

MATLAB R2021a was used for the simulations and implementations of these algorithms. First, integer shift envelope correlation algorithms were applied. With the exception of peak alignment, they are the easiest to implement. Despite being easier, the peak alignment would produce worse outcomes. The algorithms were implemented in the following order:

- The envelope correlation approach, often known as the single reference profile, was the first algorithm to be used. This approach is easy to use. Every other unaligned profile is aligned using a single reference profile that is selected.
- The adjacent reference profile envelope correlation algorithm was the second algorithm used. Because the reference profile is always changing, this method is an improvement over the previous one. This implies that the reference profile is kept as current as possible by using the previously aligned profile when aligning a new profile.
- The alignment algorithm for the non-coherent envelope correlation was implemented next. It is beneficial to use an average of all aligned profiles before aligning a profile because this filters out errors caused by a small percentage of profiles. As a result, an improvement over the prior algorithm was anticipated in this area.
- Finally, the alignment procedure known as the sliding-window average reference profile (envelope correlation) was applied. The algorithm that was previously explained is improved by this one. Here,

a sliding window with a limited number of previously aligned profiles is used rather than the average of all previous algorithms. This lowers the likelihood of error propagation and makes the average unaligned profile more current.

3.3.2 Sub-integer shift range alignment algorithms

This approach has similarities to the integer shift algorithms described above. With the exception of using the sub-integer versions of the techniques, the range alignment algorithms are performed in the same order as in Chapter 3.3.1. Below is the order:

1. Single reference profile (envelope correlation method) alignment algorithm [Sub-integer shift]
2. Adjacent reference profile (envelope correlation) alignment algorithm [Sub-integer shift]
3. Non-coherent Cumulative Average Reference Profile (envelope correlation) alignment algorithm [Sub-integer shift]
4. Sliding-Window Average reference profile (envelope correlation) alignment algorithm [Sub-integer shift]

To determine the shifts needed for each algorithm, the sub-integer shift algorithms' associated integer shift algorithms were first implemented. A low-order polynomial curve was fitted to the set of integer shifts after the shifts needed for each profile were established for each profile. As a result, each profile has a set of sub-integer shifts. The profiles that had previously been aligned (using integer shift techniques) were once more "aligned," but this time with sub-integer shifts.

3.3.3 The quality measures

The contrast [4] and entropy [4], [25] are the two measures of quality that were investigated. These metrics were selected because of their reliability and simplicity. They are less susceptible to target fluctuations than the other methods, and they are also thoroughly described in the literature. Although these metrics may favour larger and more diverse datasets, this may be explained by normalising the data and dividing the obtained values by the datasets' sizes.

Since the sum envelope's value was required for both measures, it was computed (using Equation 2.16) before the contrast and entropy could be reached.

i. Contrast

Equation 2.17 was used to calculate the contrast. The MATLAB sum function was applied in this case. Equation 2.18 was then used to convert the result to the logarithmic scale.

ii. Entropy

Equation 2.19 was then used to calculate the entropy. Again, the MATLAB sum function was utilised.

iii. Qualitative measure

Notably, the range alignment algorithms were also examined by merely examining the HRR profiles to determine how well they aligned.

3.3.4 Dataset Testing

The algorithms previously described were used across the CSIR datasets. Each algorithm's results are displayed under the same sub-chapter. Additionally, a comparison of each algorithm's performance across the various datasets is provided. Both the visual results and quality metrics like contrast and entropy are included in the results.

Additionally, several blocks of profiles within the CSIR dataset were compared. This is a result of the dataset's significant variation across various profile blocks.

3.3.5 HRR profile and bin shift plots

The results show three different types of plots. These include bin shift charts, HRR profile plots, and quality measure comparison plots.

i. HRR profile plots

A qualitative assessment of the profiles' alignment is provided by the HRR plots. The plots, which display the distribution of each profile's scatterers across the range bins, have a specified range on the x-axis and the profile number on the y-axis. Dominant scatterers and the size of the remaining scatterers are visually highlighted using a colour bar. A logarithmic (dB) scale was used to plot the profiles' amplitudes based on their magnitude.

ii. Bin shift plots

The profile number is plotted against the necessary shift for alignment in these figures. The necessary bin shift is on the y-axis, while the profile number is on the x-axis. They typically create a staircase shape, suggesting that profiles that are closer together are typically not distinct enough to necessitate "integer" shifts.

The bin shift graphs are displayed using a fitted polynomial to depict the sub-integer shifts when using sub-integer shift methods.

iii. Quality measure comparison plots

These charts demonstrate how the contrast and entropy that come from using various data blocks (in the CSIR dataset) change. Consequently, the plots display the contrast/entropy (in dB) on the y-axis and the blocks on the x-axis.

3.3.6 Dominant Scatterer Autofocus

Once range alignment is completed, the first autofocus method, the dominant scatterer technique, which was described in Chapter 2, is implemented. The results of this method are then analysed before moving on to the next algorithm.

3.3.7 Weighted multiple scatterer (Yuan) Autofocus method

Next, the weighted multiple scatterer (Yuan) autofocus algorithm is applied to the same range-aligned profiles for comparison. The results of this method are then analysed with a comparison to the results of the previous method.

3.3.8 Combination of the algorithms

The combination of the range algorithms in conjunction with the autofocus function results in finding the best ITWSP. The different combinations are shown in Table 3.5. The range alignment algorithms relate to the envelope correlation algorithms, respectively.

Table 3.5 Combination of algorithms

Integer Shift Range Alignment & Dominant Scatterer Autofocus	Sub-integer Shift Range Alignment & Dominant Scatterer Autofocus
Integer Shift Range Alignment & Weighted Multiple Scatterer (Yuan) Autofocus	Sub-integer Shift Range Alignment & Weighted Multiple Scatterer (Yuan) Autofocus

Using the quality measures discussed previously, such as the contrast and entropy, as well as analysing the resulting ISAR images, determines the quality of the combination.

3.4 Overview of the selection of the algorithms to identify effective imaging intervals

A focused ISAR image, which is useful for classification, may be generated when a vessel has a specific 2D rotation motion over the CPI. Not all ISAR images contain useful information for classification. Some images are too blurry and distorted for classification. Algorithms have been published in the literature to identify effective imaging intervals. In this work, two algorithms that identify optimum imaging intervals are applied to measured data, and their performance is compared. The better-performing algorithm was selected for integration into the ITWSP. The first algorithm used was the MC-ATWS technique. The second algorithm was the Optimal CPI Selection based on Image Contrast Optimisation and Doppler Spread technique.

4. Verification of translation motion compensation algorithms using Simulations

Translation motion compensation algorithms were initially applied to simulated data for verification purposes before they were applied to measured data. This chapter describes the simulation environment that was developed to generate synthetic high-range resolution profiles of a vessel, which was represented as a set of point-scatterers. The simulation allows for the generation of simulated radar data with known input radar and target parameter values. The radar simulator uses a stepped frequency waveform to generate high-range resolution profiles, similar to the technique used in the experimental X-band Pulse-Doppler radar discussed in Section 3.2 to measure sea vessels.

4.1 Stepped Frequency Waveforms

SFWs are used to produce synthetic HRR target profiles. The process is outlined in Wehner [36] and is summarised in the following steps: [37]

1. Firstly, a sequence of N narrow-band pulses is transmitted, where the centre frequency of successive pulses changes by a fixed frequency step, Δf . Every collection of n pulses is called a burst.
2. For each transmitted pulse, the received signal is mixed down to the baseband, the in-phase and quadrature components are sampled at the bandwidth of the narrow-band pulse, and matched filtering is performed to increase the SNR.
3. Next, the n target echoes from a burst are stored.
4. The complex-valued target echoes from n pulses are subjected to spectral weighting to lower the range sidelobe level. Adjustments are made for the target's translation motion in the burst.
5. Lastly, a synthetic HRR profile is created by applying the Inverse Discrete Fourier Transformation (IDFT) to the weighted quadrature components.
6. To create N synthetic HRR profiles, the procedure outlined in steps 1 to 5 is repeated for N bursts.

An SFW burst is depicted in Fig 4.1. The PRI is T and the pulse width is τ' . The centre frequency for the i^{th} step is described in Equation 4.1.

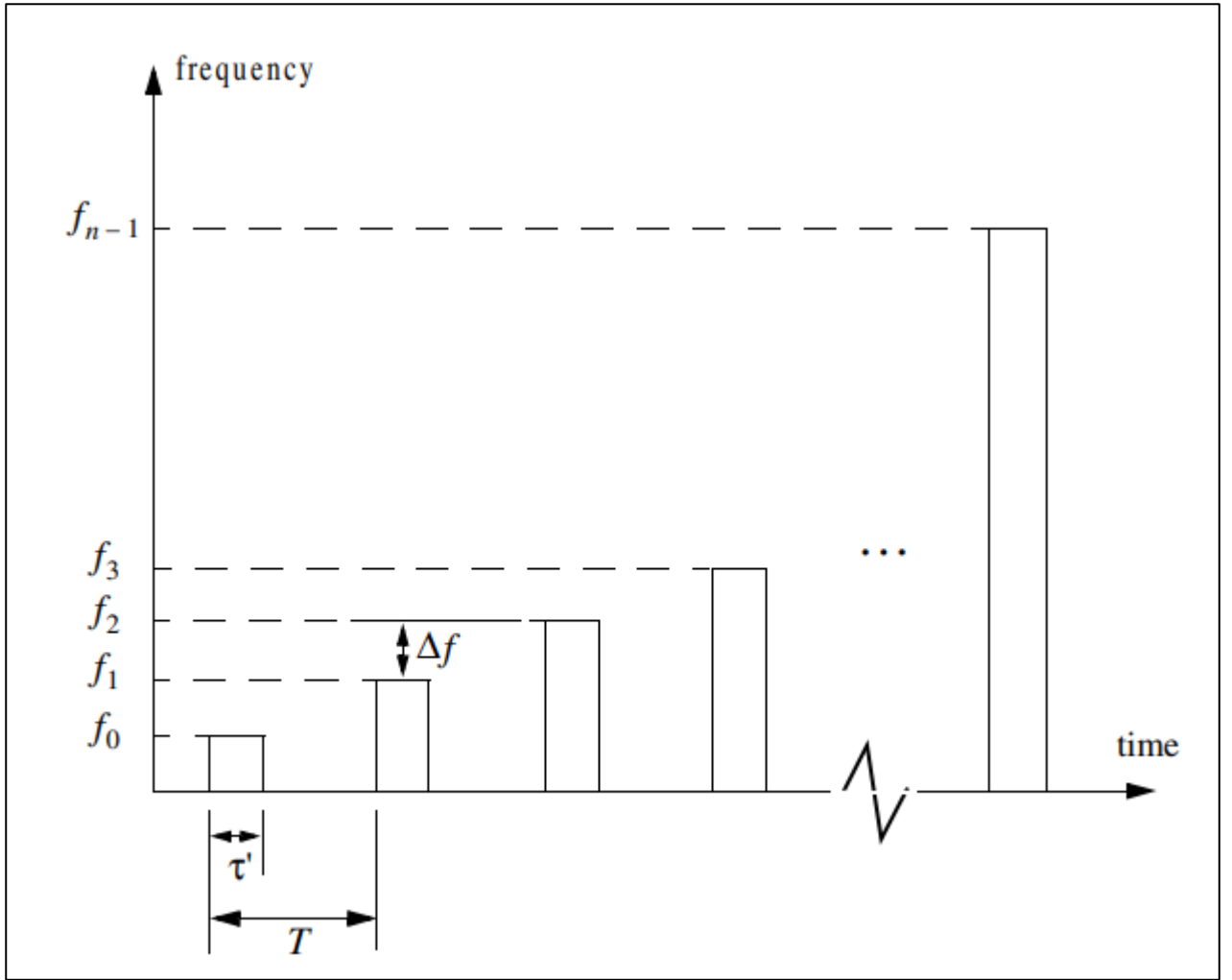


Figure 4.1 Stepped frequency waveform burst

Equation 4.2 describes the transmitted waveform for the i^{th} step within a burst, where C_i are constants and θ_i are the relative phases. Equation 4.3 provides the received signal from a target at a range, R_0 , at time $t = 0$, where C_i' is constant. Equation 4.4 provides the round-trip delay $\tau(t)$. The target radial velocity is v , while the speed of light is c .

$$f_i = f_0 + i\Delta f \quad ; i = 0, n-1 \quad (4.1)$$

$$s_i(t) = \begin{cases} C_i \cos 2\pi f_i t + \theta_i & iT \leq t \leq iT + \tau' \\ 0 & ; \text{elsewhere} \end{cases} \quad (4.2)$$

$$s_{ri}(t) = C_i' \cos (2\pi f_i (t - \tau(t)) + \theta_i \quad ; iT + \tau(t) \leq t \leq iT + \tau' + \tau(t) \quad (4.3)$$

$$\tau(t) = \frac{R_0 - vt}{c/2} \quad (4.4)$$

To extract the quadrature components, the received signal is down-converted to the base band. More specifically, in Equation 4.5, $s_{ri}(t)$ is combined with the signal. After low-pass filtering, the quadrature components are given by Equation 4.6 where A_i are constants, and Ψ_i is described in Equation 4.7 and $f_i = \Delta f$. The quadrature components are then sampled for each pulse at the rate shown in Equation 4.8. τ_r is the range-related time delay that marks the beginning of the range profile. Equation 4.9 illustrates how the quadrature components can subsequently be stated in complex form [37].

$$y_i(t) = C \cos(2\pi f_i t + \theta_i) \quad ; iT \leq t \leq iT + \tau' \quad (4.5)$$

$$\begin{pmatrix} x_1(t) \\ x_Q(t) \end{pmatrix} = \begin{pmatrix} A_i \cos \Psi_i(t) \\ A_i \sin \Psi_i(t) \end{pmatrix} \quad (4.6)$$

$$\Psi_i(t) = -2\pi f_i \left(\frac{2R_0}{c} - \frac{2vt}{c} \right) \quad (4.7)$$

$$t_i = iT + \tau_r + \frac{2R_0}{c} \quad (4.8)$$

$$X_i = A_i e^{j\Psi_i} \quad (4.9)$$

Samples of the target reflectivity in the frequency domain caused by a single burst are shown in Equation 4.9. The IDFT can then be used to convert this data into a set of range delay reflectivity (also known as range profile) values. Equation 4.10 follows from that. [37]

$$H_l(t) = \frac{1}{n} \sum_{i=0}^{n-1} X_i \exp\left(j \frac{2\pi l i}{n}\right) \quad ; 0 \leq l \leq n-1 \quad (4.10)$$

Equation 4.11 is a result of substituting Equation 4.9 and Equation 4.7 into Equation 4.10.

$$H_l(t) = \frac{1}{n} \sum_{i=0}^{n-1} A_i \exp\left\{j \left(\frac{2\pi l i}{n} - 2\pi f_i \left(\frac{2R_0}{c} - \frac{2vt_i}{c} \right) \right)\right\} \quad (4.11)$$

Equation 4.11 can then be written as seen in Equation 4.12 when normalising with respect to n and assuming $A_i = 1$ and that the target is stationary ($v = 0$) [37].

$$H_l(t) = \sum_{i=0}^{n-1} \exp \left\{ j \left(\frac{2\pi l i}{n} - 2\pi f_i \frac{2R_0}{c} \right) \right\} \quad (4.12)$$

Using $f_i = i\Delta f$ inside Equation 4.12 yields Equation 4.13. This is further simplified in Equation 4.14 where χ is defined in Equation 4.15 [37].

$$H_l(t) = \sum_{i=0}^{n-1} \exp \left\{ j \frac{2\pi i}{n} \left(-\frac{2nR_0\Delta f}{c} + l \right) \right\} \quad (4.13)$$

$$H_l = \frac{\sin \pi \chi}{\sin \frac{\pi \chi}{n}} \exp \left(j \frac{n-1}{2} - \frac{2\pi \chi}{n} \right) \quad (4.14)$$

$$\chi = \frac{-2nR_0\Delta f}{c} + l \quad (4.15)$$

Lastly, the synthesised range profile is described in Equation 4.16 [37].

$$|H_l| = \left| \frac{\sin \pi \chi}{\sin \frac{\pi \chi}{n}} \right| \quad (4.16)$$

4.1.1 Range Resolution and Range Ambiguity in SFW

The total bandwidth of n transmitted pulses is used to calculate range resolution. Using an SFW with n steps and a step size of Δf , the corresponding range resolution of the HRR profile is described by Equation 4.17 [37].

$$\Delta R = \frac{c}{2n\Delta f} \quad (4.17)$$

The phase term corresponding to a point scatterer located range R_0 can be used to identify range ambiguity associated with an SFW. This is seen in Equation 4.18 [37].

$$\Psi_i(t) = 2\pi f_i \frac{2R_0}{c} \quad (4.18)$$

Equation 4.19 follows from the above, which is then simplified in Equation 4.20.

$$\frac{\Delta \Psi}{\Delta f} = \frac{4\pi(f_{i+1} - f_i) R_0}{(f_{i+1} - f_i) c} = \frac{4\pi R_0}{c} \quad (4.19)$$

$$R_0 = \frac{\Delta\Psi}{\Delta f} \frac{c}{4\pi} \quad (4.20)$$

Clearly, from Equation 4.20 it is seen that range ambiguity exists for $\Delta\Psi = \Delta\Psi + 2n\pi$ and therefore R_0 can be written as seen in Equation 4.21 with the unambiguous range window, R_u , shown in Equation 4.22 [37].

$$R_0 = \frac{\Delta\Psi + 2n\pi}{\Delta f} \frac{c}{4\pi} = R_0 + n \left(\frac{c}{2\Delta f} \right) \quad (4.21)$$

$$R_u = \frac{c}{2\Delta f} \quad (4.22)$$

Therefore, the relative range reflectivity for all scatterers within the unambiguous range window, with respect to the absolute range that corresponds to the burst time delay, is represented by a range profile synthesised using a specific SFW.

Furthermore, all scatterers falling outside the unambiguous range window fold over and show up in the synthesised profile if a particular target extent is greater than R_u . The spectral foldover that happens when a Fourier Transform is used to determine certain signal frequency contents is the same as this foldover problem.

Therefore, the frequency step Δf must meet the criteria in Equation 4.23 to prevent foldover in the synthesised range profile. E is the target extension in meters [37].

$$\Delta f \leq \frac{c}{2E} \quad (4.23)$$

Furthermore, the pulse width needs to be sufficiently wide to include the entire target extent. Consequently, this is expressed in Equation 4.24 which is translated to Equation 4.25 in practice. This reduces the clutter-to-noise ratio in the synthesised range profile. [37]

$$\Delta f \leq \frac{1}{\tau'} \quad (4.24)$$

$$\Delta f \leq \frac{1}{2\tau'} \quad (4.25)$$

4.1.2 Effect of Target Velocity

Equation 4.16 assumes that the target is stationary in a burst. To assess the impact of target velocity in the burst on the synthesised range profile, Equation 4.7 and Equation 4.8 can be substituted into Equation 4.10, providing Equation 4.26 following normalisation. The synthesised range profile is distorted by the extra phase term seen in Equation 4.26 [37].

$$H_l = \sum_{i=0}^{n-1} \exp \left\{ j \frac{2\pi l i}{n} - j 2\pi f_i \left[\frac{2R}{c} - \frac{2v}{c} \left(iT + \frac{\tau_1}{2} + \frac{2R}{c} \right) \right] \right\} \quad (4.26)$$

By multiplying the complex received data at each pulse by the phase term Φ in Equation 4.27, where $\underline{v}$ and $\underline{R}$ are estimations of the target velocity and range, respectively, this distortion can be removed.

$$\Phi = \exp\left(-j2\pi f_i \left[\frac{2v}{c}\left(iT + \frac{\tau_1}{2} + \frac{2R}{c}\right)\right]\right) \quad (4.27)$$

Phase rotation is a common term used to describe the act of altering the quadrature components' phase. In some applications, frequency hopping between the successive pulses inside the SFW is used to lessen the impacts of target velocity when accurate predictions of $\underline{v}$ and $\underline{R}$ are unavailable. In this instance, a preset code is used to establish the frequency of each individual pulse. This kind of waveform is frequently referred to as a frequency-coded waveform [37].

4.2 Implementation and Results

The results begin with a code snippet of the algorithm which is seen in Fig. 4.2. Here the values that are set for the parameters such as initial frequency, step size, number of bursts, and the number of pulses, can be seen. Furthermore, the signal power and noise power are set. In Fig. 4.3 a plot of a simulated vessel can be seen, which is a result of the code in Fig. 4.2. The scatterers are purposely placed to represent a vessel with two masts. The image produced relates to the side view.

```

C = 3e8;                                % Speed of light
F0 = 9.5e9;                             % Initial centre frequency
DeltaF = 4e6;                           % Frequency step size
N = 256;                                % Number of pulses in burst
M = 32;                                % Number of Bursts
y=M                                     %
PRF = 2e3;                              % Pulse Repetition Frequency
SNR_dB = 40;                            % Assume signal power = 1
CentreFrequencyVector = (0:(N-1))*DeltaF + F0;
R0 = 10.106e3;                          % Distance to centre of target in km
Pn = 10^(-(SNR_dB-10*log10(N))/10);      % Noise Power

Range_Resolution = C/(2*N*DeltaF);
Unambiguous_range = (N-1)*Range_Resolution;
PRI = 1/PRF;
BurstRepetitionFrequency = PRF/N;
BurstRepetitionInterval = 1/BurstRepetitionFrequency;

TimePerBurstVector = (0:(M-1))*BurstRepetitionInterval;

TgtVelocity_ms = 0.2;                   %Ideal isar image when set to 0
RotRate_deg_s = 0.8;
%Scatterer_xy_local = [-10 0; 0 0; 7 0 ]; % Scatterer local co-ordinates
% Each row has two elements: [x-cord y-cord]

Scatterer_xy_local = [-10 0; -7 0; -3 0; 0 0; 3 0; 7 0; 10 0; -3 1; 7 1; -3 2; 7 2; -3 3; 7 3 ];
scatterer_rcs=[1 1 1 10 1 1 1 1 1 1 1 1]

```

Figure 4.2 Code Snippet for Simulation Set-up

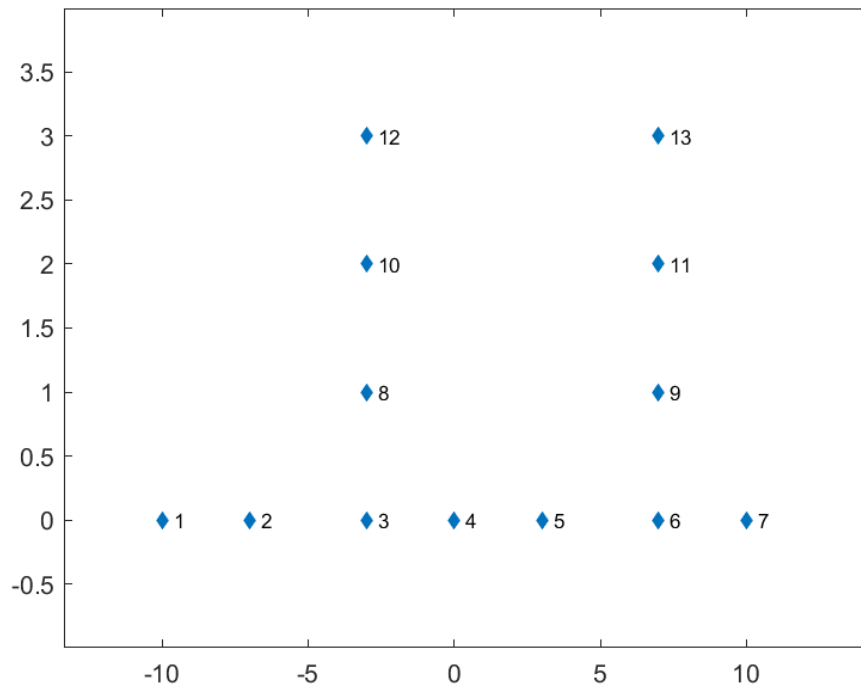


Figure 4.3 Side-view of simulated vessel

Firstly, the unaligned profiles are shown in Fig. 4.4. This refers to the radar data before any range alignment. Fig. 4.5 depicts the unfocused ISAR image that was generated without applying range alignment and autofocus. The quality measures, namely the contrast and the entropy of the images, are shown in Tables 4.1 and 4.2, respectively.

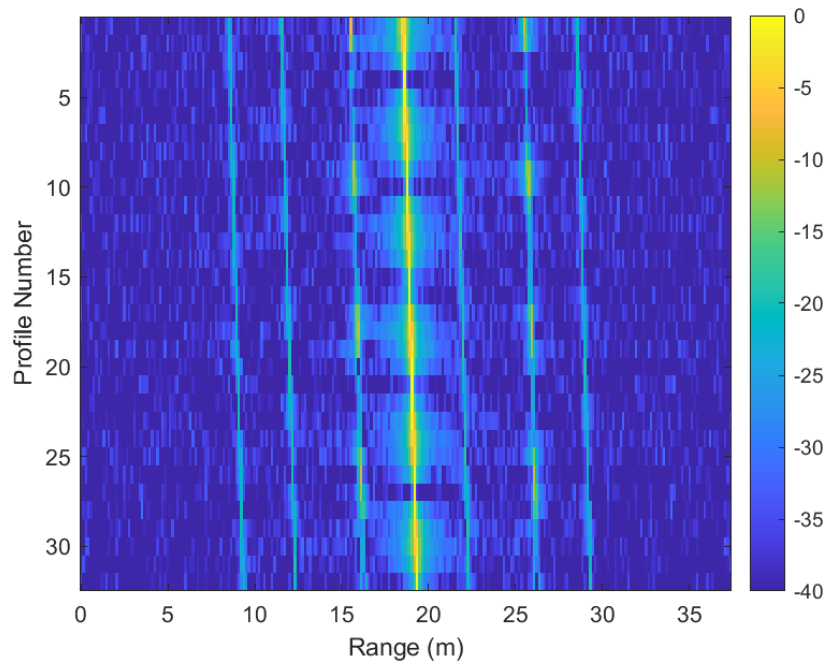


Figure 4.4 Unaligned HRR profiles

Table 4.1 Table showing the contrast and entropy values in dB

Contrast (dB)	Entropy (dB)
1.3554e+03	-131.8966

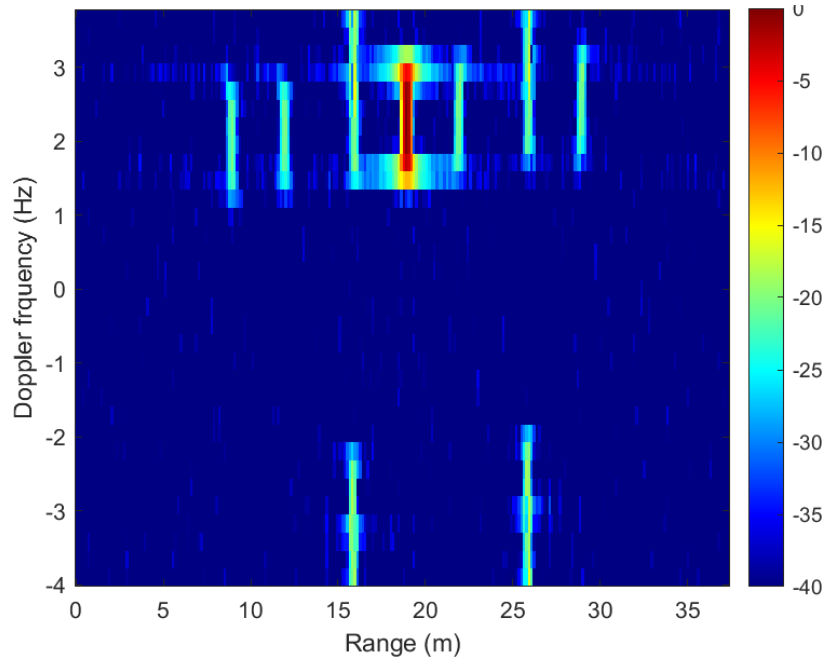


Figure 4.5 Unfocused ISAR image with no RA

Table 4.2 Table showing the contrast value in dB

Contrast (dB)
0.1566

Next, the envelope correlation integer shift range alignment was applied to the simulated HRR profiles in Fig. 4.4. This range alignment was chosen as it is more robust for measured datasets, which is analysed in Chapter 5. The flow of the algorithm is depicted in Fig. 4.6. The first step was to calculate the number of integer shifts each profile needed for alignment. This is displayed in Fig 4.7. If the profiles are close to one another, a staircase shape would result as profiles next to each other require a similar number of shifts. The steps are also indicative of the jumps in integer values, which are seen in the plot of the HRR profiles in Fig. 4.7. Plateaus seen in the staircase-shaped figure are due to using a relatively small block of profiles.

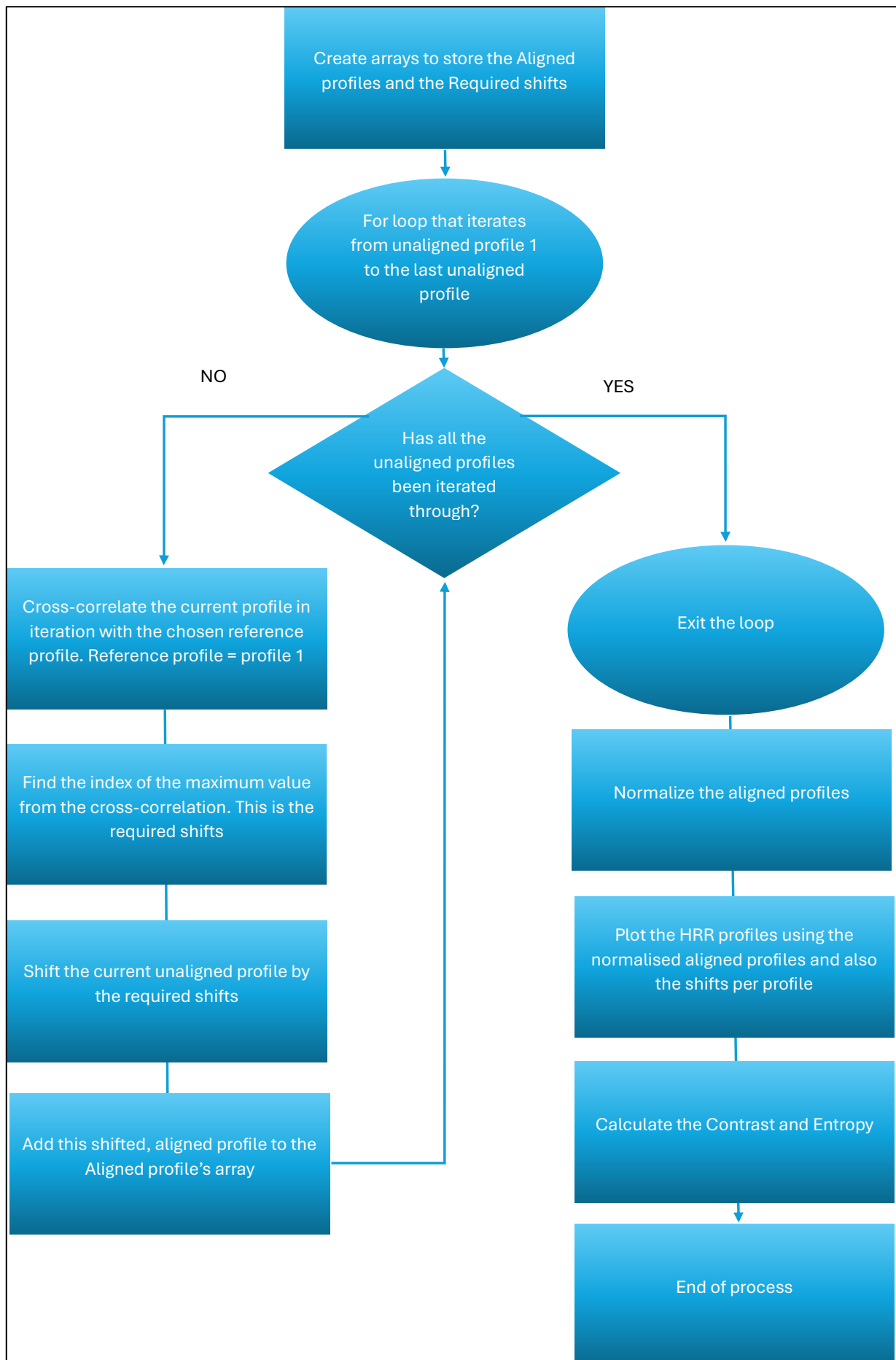


Figure 4.6 Flow of envelope correlation algorithm (Integer Shift) and quality measure step

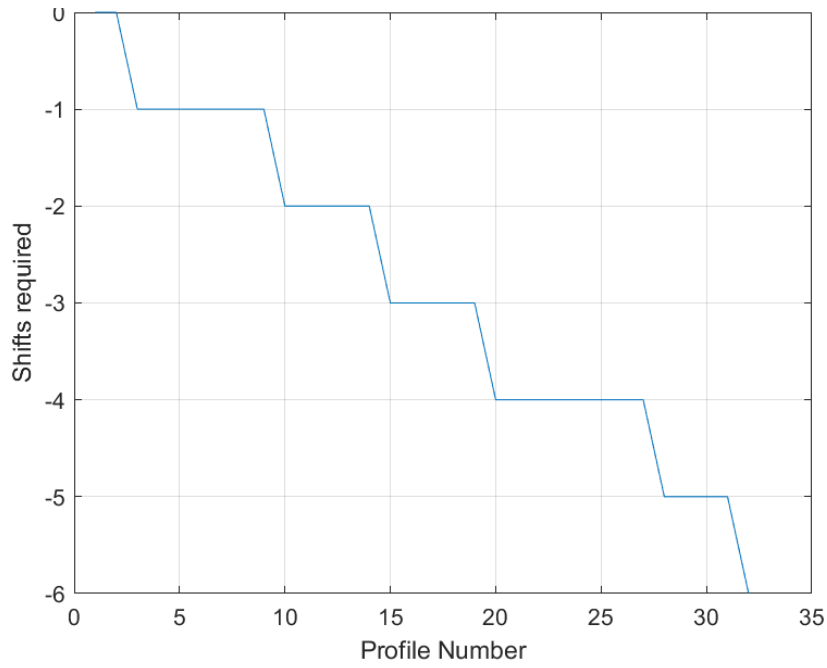


Figure 4.7 Plot of the integer bin shifts required

Fig. 4.8 illustrates the HRR profiles after range alignment. The reference profile was selected to be the first profile. The HRR profiles plot makes it evident that alignment was successful. The migration of a scatterer through range bins over the HRR profiles was lower than in the unaligned HRR profiles. The resulting unfocused ISAR image is shown in Fig. 4.9. As indicated in Tables 4.3 and 4.4, respectively, the quantitative metrics of alignment, represented by the image contrast and entropy of the ISAR image, support the qualitative measure obtained through visualising the HRR profiles.

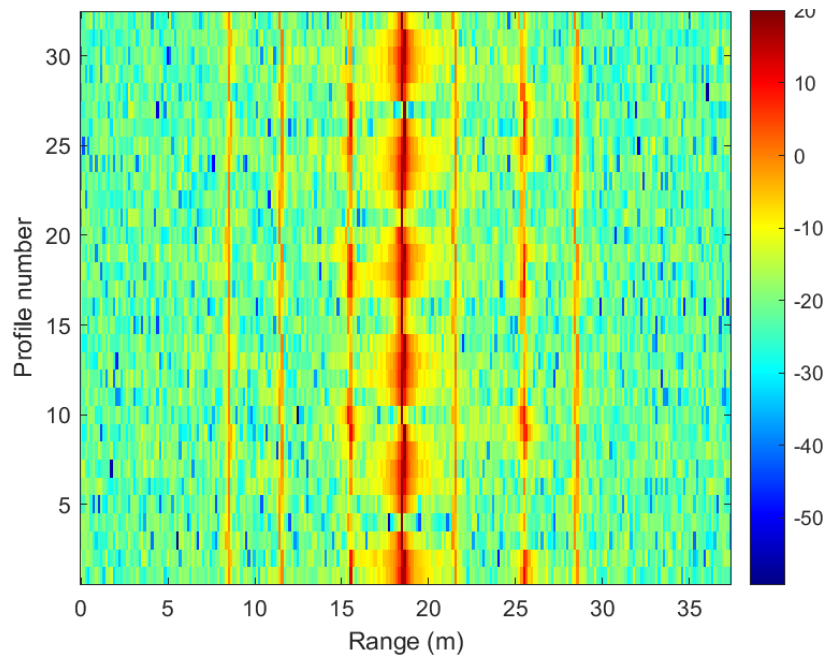


Figure 4.8 HRR profiles after integer shift range alignment

Table 4.3 Table showing the contrast value in dB

Contrast (dB)	Entropy (dB)
0.3512	0.1515

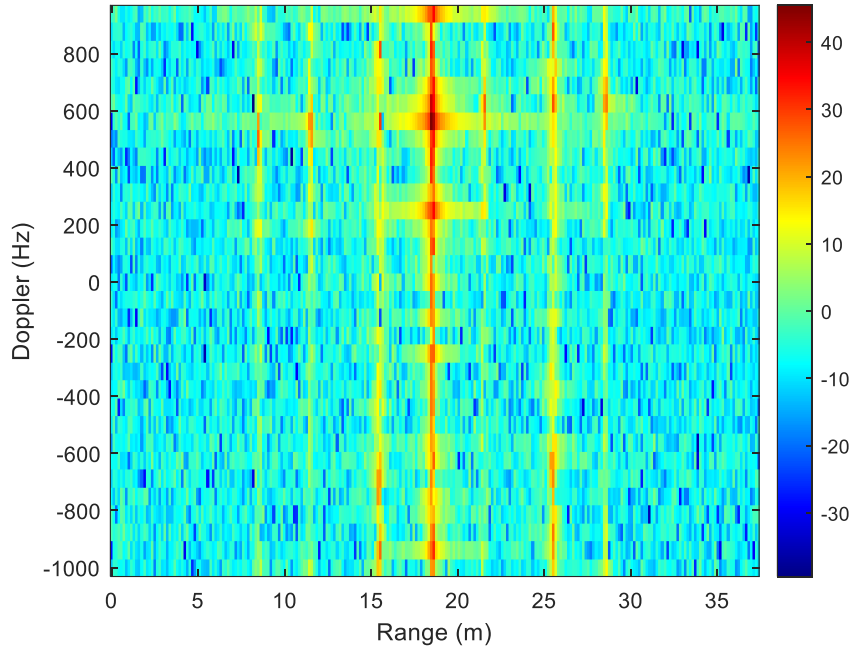


Figure 4.9 Unfocused ISAR image after integer shift range alignment

Table 4.4 Table showing the contrast value in dB

Contrast (dB)
30.5492

To improve the focus of the ISAR image, autofocus was applied to the aligned HRR profiles. The resulting ISAR image of the Dominant Scatterer algorithm is shown in Fig. 4.10 and the resulting image for the Weighted MSA is shown in Fig. 4.10. The images both do not resemble the simulated vessel in Fig. 4.3. This happens because the profiles in Fig. 4.8 are not properly aligned, which can be seen from the linear movement of scatterers across the profiles. In addition, there are several strong scatterers, noticeable by the deep red pixels spread across various range bins. One key scatterer, shown in deep red (~17-18m), does not stay fixed in the same range bin throughout the HRR profiles, highlighting the misalignment. The respective quantitative measures for Fig. 4.10 and Fig. 4.11 are given in Table 4.5 and Table 4.6. These values should be improved to indicate better alignment and better ISAR images.

The dominant scatterer autofocus algorithm described in Chapter 2 is implemented on both datasets once range alignment has taken place. The steps for Dominant Scatterer Autofocus are as follows:

1. Take the sum squared of every range bin and find the range bins that are greater than the average sum squared of all the range bins. In this step, the algorithm finds many ‘candidate’ scatterers.
2. For each ‘candidate’ scatterer, calculate the variance of the range bin, after alignment has taken place. Next, choose the candidate scatterer that has the lowest variance.

3. Calculate the phase difference between the reference bin of your reference profile and the reference bin in every other profile. Another approach is to obtain the phase history of the dominant scatterer. This is a vector.
4. Apply each difference to its respective HRRP. Multiply each HRRP by the respective phase difference. Another approach is to obtain the complex conjugate of the phase history and apply this to each range bin of the aligned profiles.

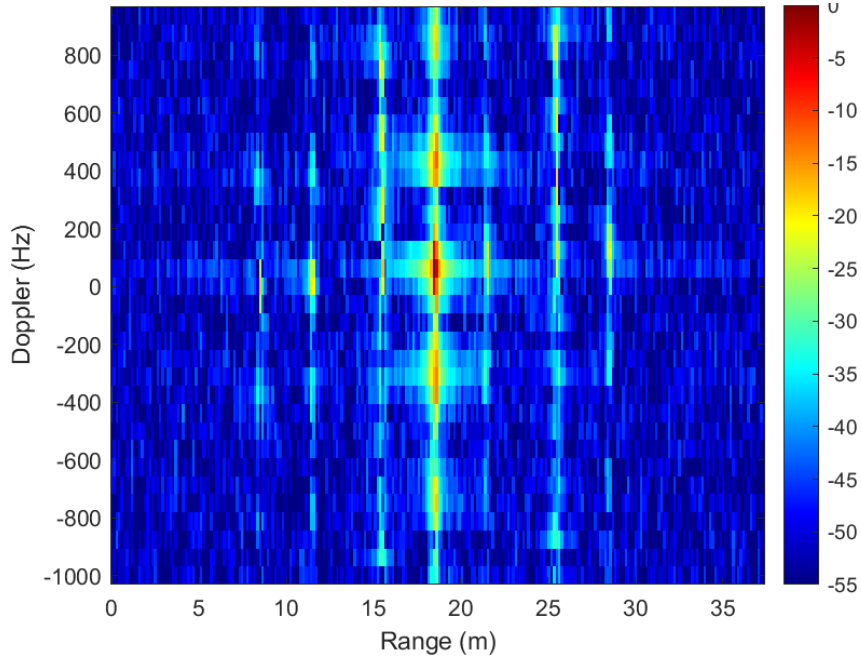


Figure 4.10 ISAR image after Dominant Scatterer Autofocus

Table 4.5 Table showing the contrast value in dB

Contrast (dB)
30.6988

Next, the weighted multiple scatterer (Yuan) autofocus algorithm, also described in Chapter 2, is implemented. A summary of the processing steps follows. The method is based on an arbitrary example for simplicity:

Consider an input-aligned range profile, matrix $\mathbf{B}_{N \times M}$, with dimensions $N \times M$, where N represents the total number of rows and M represents the total number of columns. In this case, N = total number of range profiles and M = total number of range bins. In summary, each row of the $\mathbf{B}_{N \times M}$ matrix is an aligned range profile.

The autofocus step outputs a complex phase correction vector $\mathbf{c}_{N \times 1}$, where each element is a complex number. This can be written as:

$$\mathbf{c}_{N \times 1} = [c_1 \ c_2 \ \dots \ c_N]^T \quad (\text{The transpose turns the vector into a column vector})$$

$$\mathbf{c}_{N \times 1} = \mathbf{C}_{N \times 1} \mathbf{e}^{j\phi_{N \times 1}}$$

Each element of $\mathbf{c}_{N \times 1}$ has a magnitude and a phase. Example: the first element is c_1 has a magnitude and a phase. Let the magnitude be expressed by C_1 and the phase expressed by ϕ_1 .

$$c_1 = C_1 e^{j\phi}$$

$$c_1 = a_1 + j b_1$$

a_1 is the real component of c_1 , b_1 is the imaginary component of c_1 and

$$C_1 = \sqrt{(a_1)^2 + (b_1)^2}$$

$$\phi = \text{atan}(b_1/a_1)$$

The steps below show how Yuan's autofocus algorithms obtain the vector $\phi_{Nx1} = [\phi_1 \ \phi_2 \ \phi_3 \ \phi_4 \ \dots \ \phi_N]$, which is the phase component of the complex phase correction vector c_{Nx1} .

1. Calculate the mean $m_{1 \times N}$ and variance $v_{1 \times N}$ for each column (range bin).
2. Identify the range bins that meet the criteria, $v / (v + m^2) < 0.16$. 11 scatterers are used (min= 6, max = 18). The 11 scatterers which correspond to the small values of $v / (v + m^2)$ are chosen.
3. Let the RefBins = range bins of the 1st alignment range profile that meets the criteria in step 2.

$$\text{RefBins} = \mathbf{B}_{NxM}(1, 1: 11)$$

This describes the 1st row, from range bin 1 to 11. For simplicity of describing the algorithm, it is assumed that the 11 scatterers found, correspond to range bin 1 to range bin 11.

4. Obtain the 2nd element of the phase shift vector ϕ_{Nx1} , denoted by ϕ_2 using the following computations:
 - Product_vector = conj(RefBins) .* $\mathbf{B}_{NxM}(2, 1: 11)$
 - AverageValue_scalar = sum(Product_vector)/ 11
 - $\phi_2 = \text{phase}(\text{AverageValue_scalar})$
5. Obtain the 3rd element of the phase shift vector ϕ_{Nx1} , denoted by ϕ_3 using the following computations:
 - Product_vector = conj(RefBins) .* $\mathbf{B}_{NxM}(3, 1: 11)$
 - AverageVal_scalar = sum (Product_vector)/ 11
 - $\phi_3 = \text{phase}(\text{AverageValue_scalar})$
6. Obtain the 4th, 5th ... Nth elements of the phase shift vector ϕ_{Nx1} , denoted by $\phi_4, \phi_5 \dots \phi_N$, using similar steps to Step 4 and Step 5. Then, move on to Step 7.
7. Use the phase correction vector ϕ_{Nx1} to obtain the complex phase correction vector using the formula below: Note, that magnitude is 1.

$$c_{Nx1} = e^{(-j \ \phi_{Nx1})}$$

Finally, apply the complex phase correction vector to the aligned range profiles in the same way it was applied in the Dominant Scatterer autofocus algorithm to obtain a focused ISAR image.

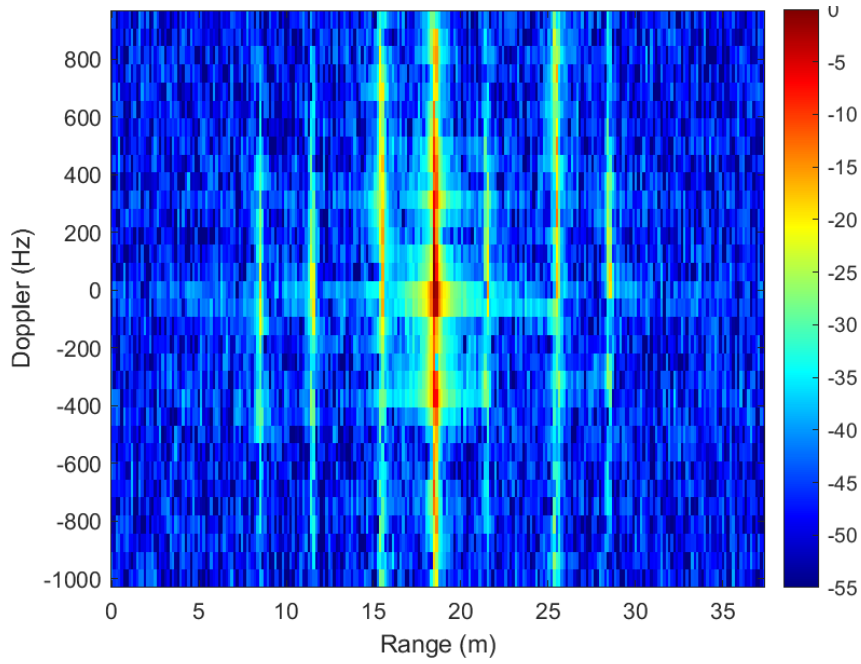


Figure 4.11 ISAR image after Weighted Multiple Scatterer Autofocus

Table 4.6 Table showing the contrast value in dB

Contrast (dB)
19.2369

The Sub-integer shift range alignment algorithm removes the periodic jumps in shifts, which was the cause of the integer shift algorithm being inefficient. In the integer shift algorithm, when a profile required a small non-integer jump for alignment, this could not be achieved. The flow of the algorithm is depicted in Fig. 4.12. This is alleviated by the sub-integer shift algorithm. A better range alignment algorithm is expected to produce a better ISAR image as errors are removed early on in the process.

Fig. 4.13 then shows the number of sub-integer shifts that each unaligned profile experienced. The second-order fitted polynomial fitter to the integer shifts, which produces the sub-integer shifts, is shown by the linear red line. Given the shape of the staircase, a negative gradient was anticipated.

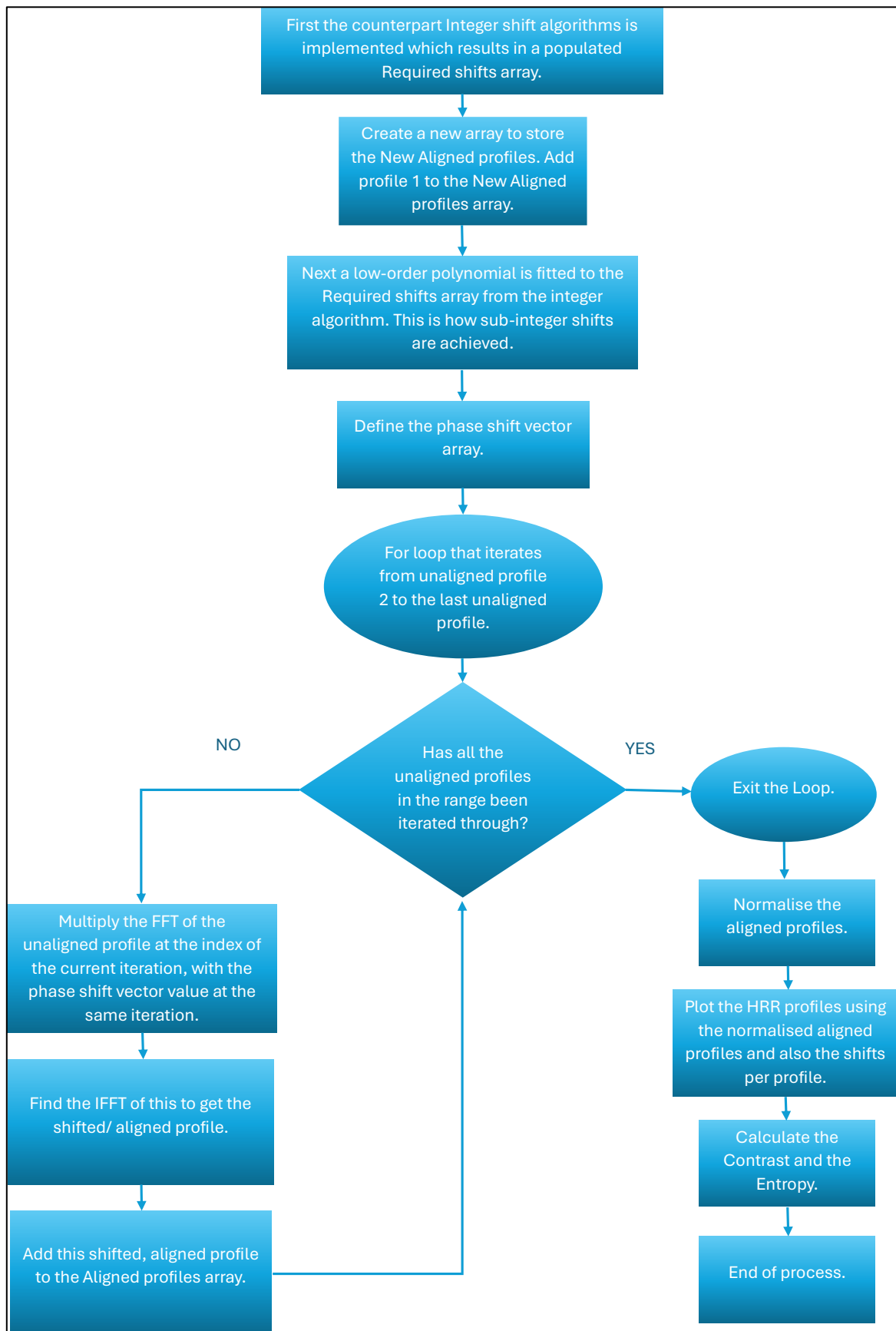


Figure 4.12 Flow of envelope correlation algorithm (Sub-integer Shift) and quality measure step

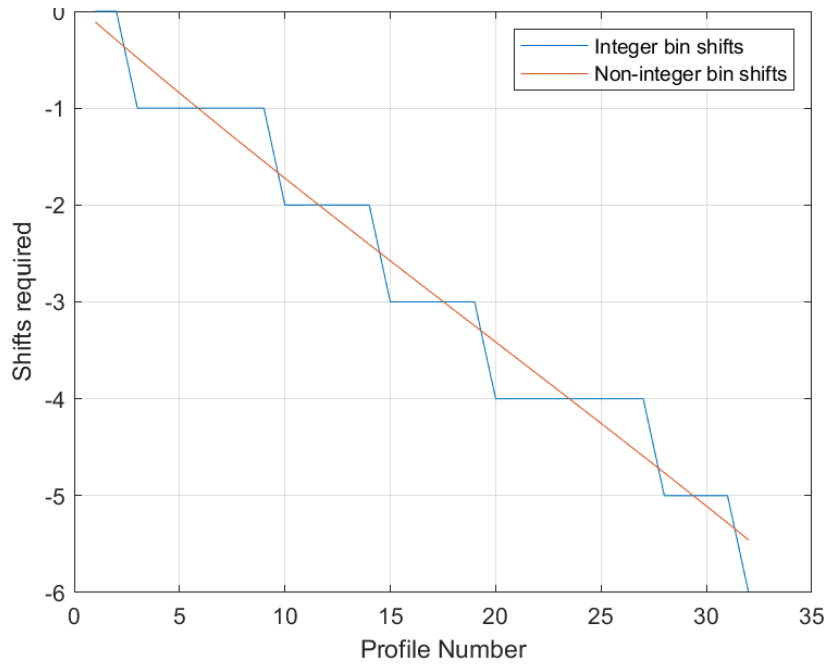


Figure 4.13 Number of shifts required per profile

Fig. 4.14 displays the new resulting range-aligned HRR profiles that were produced for the simulated dataset. The first profile was selected as the reference profile, much like in the algorithm's integer shift version. The aligned HRR profile plot makes it evident that this alignment was superior to the corresponding integer shift technique in Fig. 4.8.

Compared to Fig. 4.8, there is less scatterer migration across the range bins. Additionally, there are no longer any recurring shift jumps as there once were because sub-integer shifts are used to fix this. The scatterer at about 16 meters provides a good illustration of this visually enhanced alignment. Here, a solid deep red line is indicative of good alignment concerning the dominant scatterer. These HRR profiles appear to be the most visually compatible with the simulated dataset. Table 4.7 displays the contrast and entropy values from Fig. 4.14. Table 4.8 displays the quality metrics for the resulting unfocused ISAR image, which is displayed in Fig. 4.15.

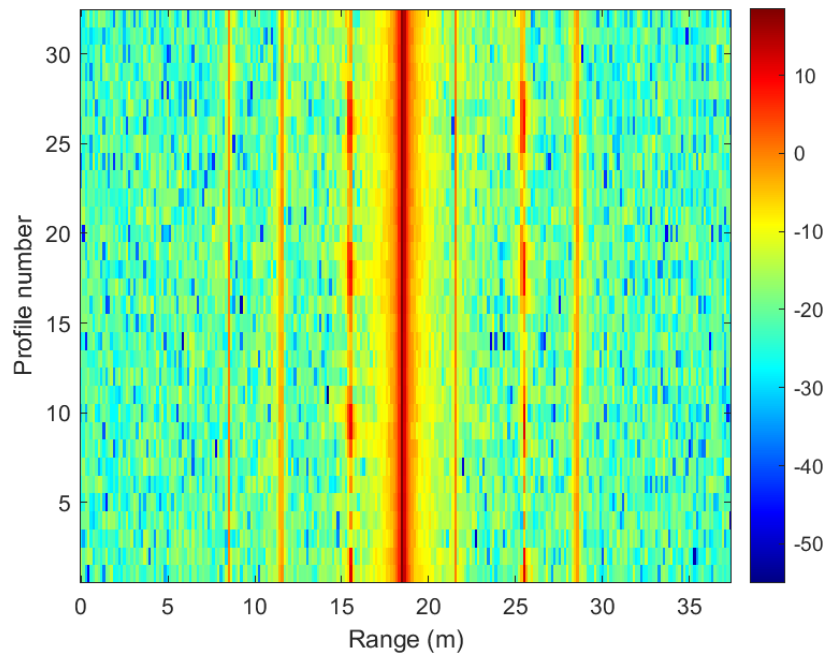


Figure 4.14 HRR profiles after sub-integer shift range alignment

Table 4.7 Table showing the contrast and entropy values in dB

Contrast (dB)	Entropy (dB)
0.4305	0.1359

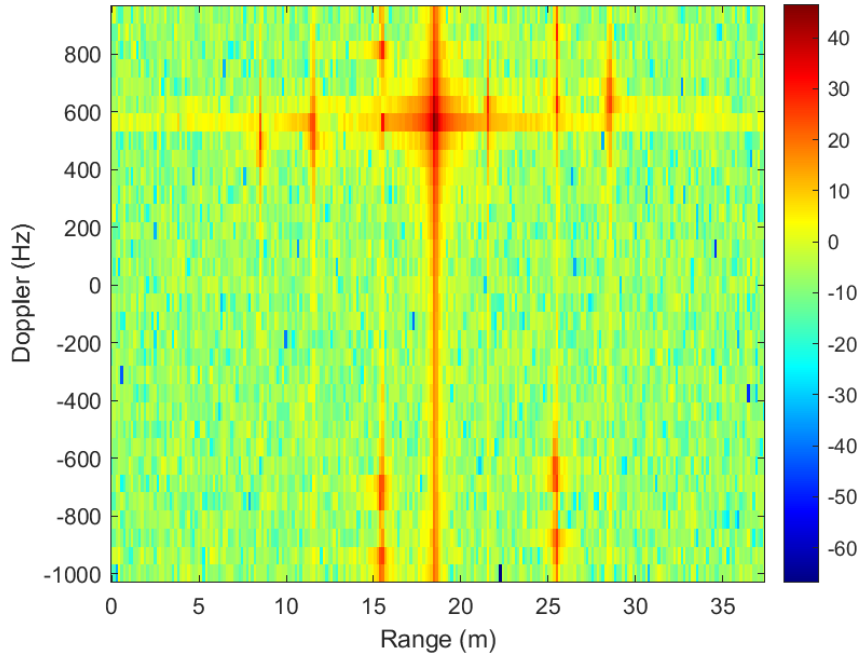


Figure 4.15 Unfocused ISAR image after sub-integer shift range alignment

Table 4.8 Table showing the contrast value in dB

Contrast (dB)
38.3653

Lastly, the focused ISAR images are produced after sub-integer shift range alignment. The resulting ISAR image of the Dominant Scatterer algorithm is shown in Fig. 4.16, and the resulting image for the Weighted MSA is shown in Fig. 4.17. Their respective quantitative measures are given in Table 4.9 and Table 4.10.

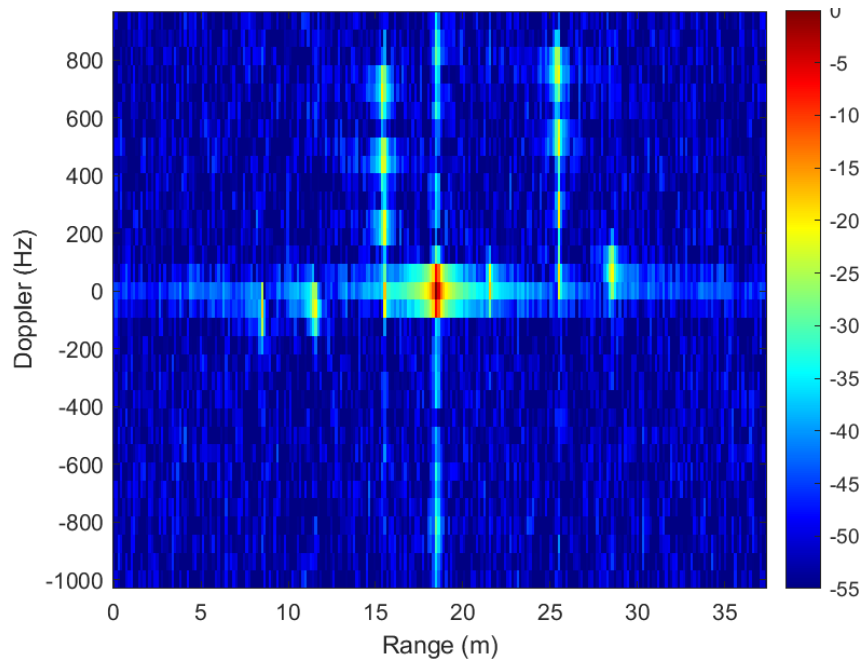


Figure 4.16 ISAR image after Dominant Scatterer Autofocus

Table 4.9 Table showing the contrast value in dB

Contrast (dB)
39.8790

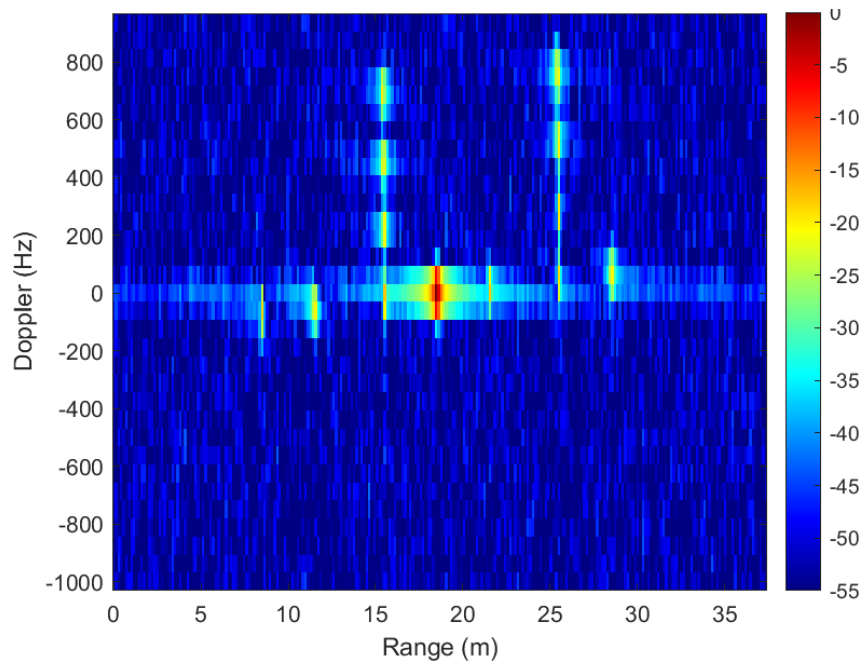


Figure 4.17 ISAR image after Weighted Multiple Scatterer Autofocus

Table 4.10 Table showing the contrast value in dB

Contrast (dB)
39.9626

Based on the results, it is evident that the sub-integer shift range alignment algorithm performs better than the integer shift algorithm. This is seen both visually and by the quality parameters. The image contrast of the sub-integer HRR profiles plot is higher (0.4305 as opposed to 0.3512) than the integer shift plot. Furthermore, the latter has a higher entropy value (0.1515 as opposed to 0.1359), indicating worse alignment.

A better range alignment results in a better overall ISAR image. Comparing the two autofocus functions after sub-integer shift range alignment, the Weighted MSA produces a visually better image. This is further justified by it having a higher contrast value (39.9626) than the image produced by the Dominant scatterer autofocus algorithm (39.8790).

4.3 Conclusion

The chapter presented the results of translation motion compensation algorithms on simulated data. A verification of translation motion compensation algorithms, on simulated data, was the core focus of the chapter.

To conclude, translation motion compensation algorithms were first applied to simulated data to confirm their effectiveness before moving on to real radar measurements. This chapter detailed the simulation setup that was created to produce synthetic high-range resolution profiles of a vessel, modelled using point scatterers. The simulation environment made it possible to generate radar data with known radar and target parameters, giving full control over the inputs. It used a stepped frequency waveform, similar to the one used by the experimental X-band Pulse-Doppler radar discussed in Section 3.2, to replicate the way sea vessels are measured in practice.

5. Translation Motion Compensation Results

The following chapter presents the range alignment and autofocus techniques discussed in Chapter 2 and Chapter 3. The results after implementing the algorithms on both maritime vessels are given. This includes both the images produced as well as the quality measures to assess the performance of the techniques. The goal of this chapter is to select the best-performing range alignment and autofocus technique for the ITWSP discussed in the preceding chapters.

The following chapter describes the high-level processing steps of all the discussed algorithms identified in Chapter 3. For each algorithm, the results of the implementations are shown for both measured datasets, that is, the CSIR datasets, to select the best range alignment and autofocus algorithm for the ITWSP. The results include the unaligned and range-aligned HRR profiles plots, bin shift plots, and the contrast and entropy values.

5.1 Range Alignment Techniques

The range alignment algorithm used to produce the results in Chapter 5.1.1 and Chapter 5.1.2 is the envelope correlation integer and sub-integer technique. This is due to this algorithm being efficient as well as producing favourable results. A comparison was done on the Zayaan vessel dataset to assess the performance of the different range alignment algorithms for different subsets within the larger dataset. This can be seen in Appendix D. A high-level processing flow for the integer shift range alignment is depicted in Fig. 5.1. The first profile is chosen as the reference profile for the algorithm. Further techniques presented, such as Autofocus in Chapter 5.2 and time window length optimisation in Chapter 6, all rely on the envelope correlation technique that follows.

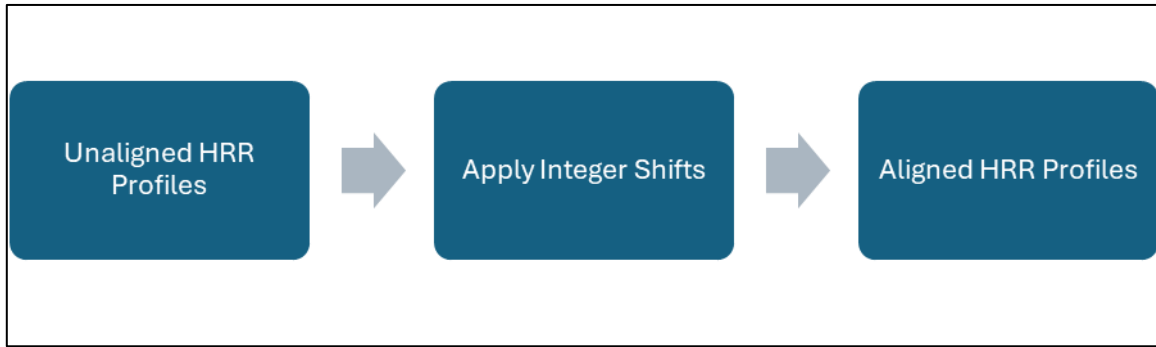


Figure 5.1 High-level processing steps for integer shift range alignment

The unaligned profiles are shown in Fig. 5.2 and Fig. 5.3, for the single-mast yacht, called the Umoya Omusha, and the fishing boat, referred to as Zayaan, respectively. This is before applying any translation motion compensation.

In Fig. 5.2. for the Umoya vessel, the “Umoya 1A” data recording is displayed. For the Zayaan vessel displayed in Fig. 5.3, the “Zayaan 1A” data recording is shown. Although the algorithms were tested across 3 data recordings, the ones above were chosen for analysis to summarise the performance.

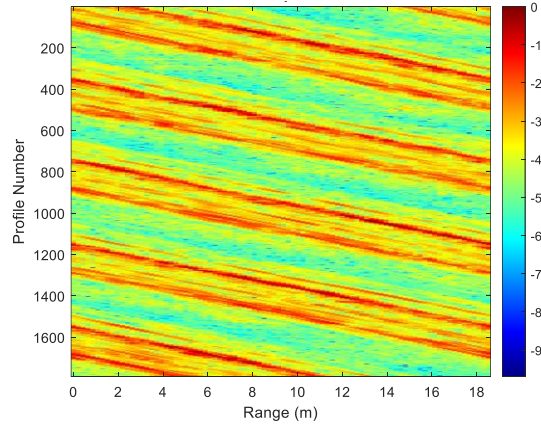


Figure 5.2 All of the HRR Profiles for the Umoya data recording

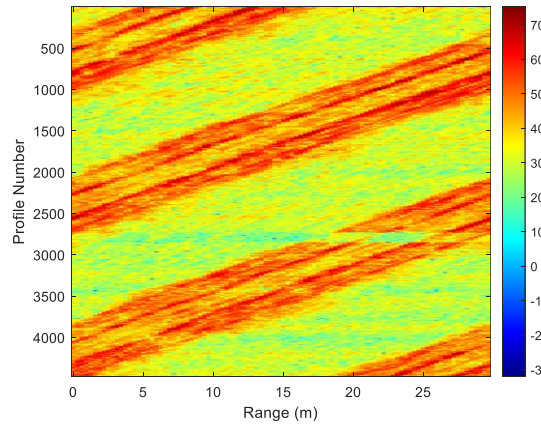


Figure 5.3 All of the HRR Profiles for the Zayaan data recording

Each data recording is further separated into 3 subsets based on different middle profiles manually chosen by sifting through the data, as at this point, there was no automated procedure. The importance of choosing a good middle profile and the automation thereof is determined here, providing the basis for the chapters that follow.

Computing the Contrast and Entropy of HRR profiles

The contrast and entropy metrics are helpful to evaluate the performance of a range alignment technique. This section discusses the steps used to calculate the entropy and contrast values. The first step is to use Equation 2.16 [17] to calculate the sum envelope, $S(n)$. These quality measurements were selected due to the justifications outlined in Chapter 3. This was accomplished in MATLAB by adding up each column's absolute HRR profile values array. A two-dimensional array is made up of the HRR profiles, with the rows denoting the profile number, and the range bins are represented by the columns. This produced a single row, with each column representing the sum of the values in each row's columns. To ensure a fair comparison of the value across datasets of varying sizes, the total envelope was divided by the number of profiles.

Equation 2.17 was used to calculate the contrast now that the sum envelope was provided. After that, the column values of the single row of values ($S(n)$) were squared and added together. The contrast is the single value that was produced as a result. To ensure a fair comparison of the value among datasets of varying sizes, the contrast was divided by the number of range bins.

Equation 2.19 was used to compute the entropy. Before being added together, the column values of the single row of data ($S(n)$) were now multiplied by their logarithm (base 10). A single value known as the entropy was obtained by multiplying the result by -1. To ensure a fair comparison of the value across datasets of varying sizes, the entropy was divided by the number of range bins. Significant peaks show up in average profiles

when profiles are properly aligned, resulting in smaller variances. As a result, the entropy value would decrease. Thus, better alignment is indicated by a decreased entropy number. Normalisation was employed to accurately compare values across different datasets because, as previously stated, both the contrast and entropy values rely on the data.

Both the entropy and contrast values were converted to the logarithmic (dB) scale for simpler reading. This was accomplished by simply multiplying the previously obtained values by 10 and obtaining their logarithm (base 10). Equation 2.18 previously demonstrated this.

5.1.1 Integer Shift (Envelope Correlation) algorithm results

The data recording of the Umoya Omusha contained approximately 1700 profiles. Three subsets of HRR profiles, each with a length of 64 profiles, were chosen to investigate the performance of translation motion compensation algorithms. These subsets of profiles were carefully selected since they gave rise to ISAR images that resembled the side view of the sea vessel. The middle profiles 180, 1010, and 1384 were manually selected as they provided favourable results. This tedious process further justifies why an automatic selection would be beneficial, especially for larger datasets. The plots of these unaligned profile sets are shown in Fig. 5.4.

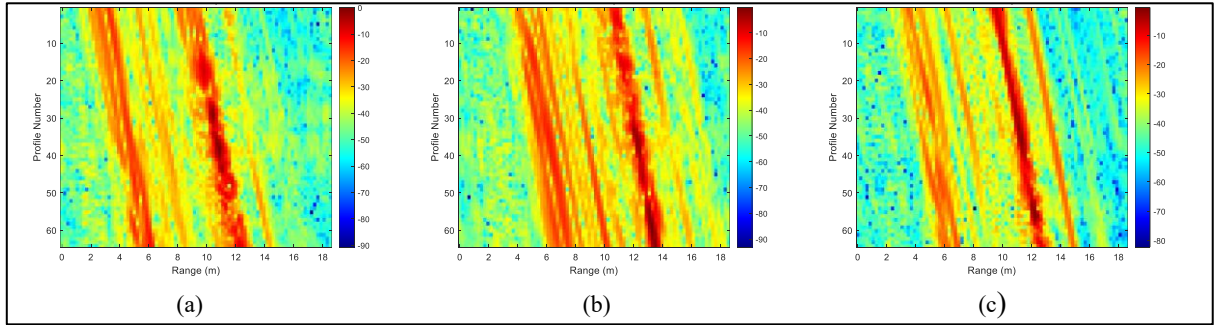


Figure 5.4 Subsets of the HRR profiles with the middle profile: (a)180, (b)1010, (c)1384

The envelope correlation range alignment algorithm was applied to each of the subsets of HRR profiles. First, the number of integer shifts each profile needs to undergo was calculated. This is displayed in Fig. 5.5. When profiles are close to each other, the staircase shape forms due to similar profiles requiring similar steps. The steps result from the jump in integer profiles as previously discussed.

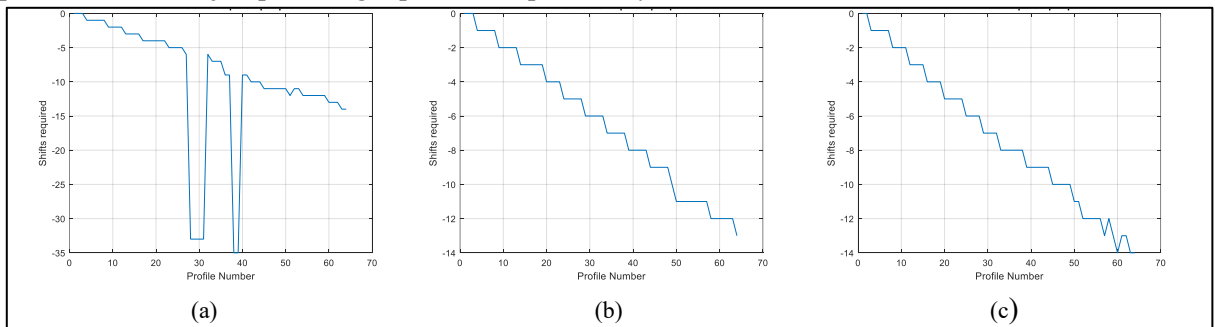


Figure 5.5 Number of shifts required per profile for middle profile: (a)180, (b)1010, (c)1384

The range-aligned HRR profiles that were produced for this dataset are shown in Fig. 5.6. Alignment has occurred, as is visually seen. Scatterer movement between range bins was lower than in the unaligned HRR profiles. The contrast is denoted by “C”, and the entropy is given by “E” on the plots. The resulting unfocused ISAR image is shown in Fig. 5.7.

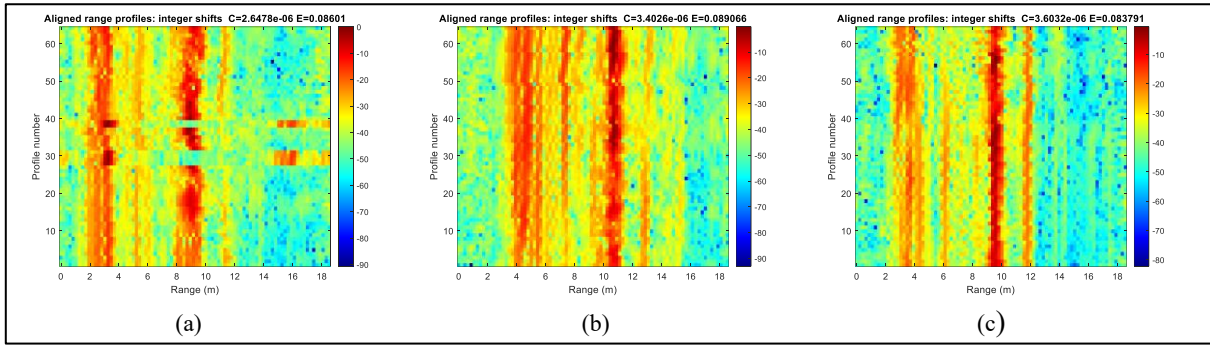


Figure 5.6 Aligned range profiles (integer shift) for middle profile: (a)180, (b)1010, (c)1384

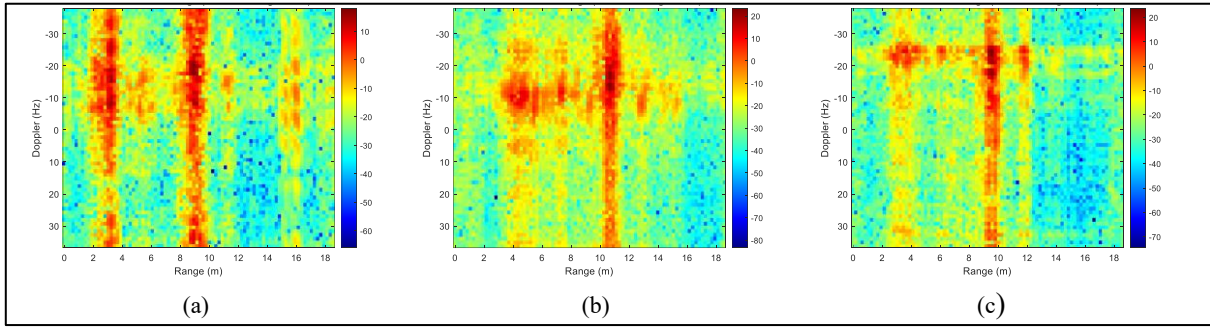


Figure 5.7 Unfocused ISAR image (with integer shift RA) for middle profile: (a)180, (b)1010, (c)1384

Similar to the data recording of the Umoya Omusha, three subsets of HRR profiles in the recording of the Zayaan vessel were identified. The middle profiles 2464, 2970, and 3827 were once again manually selected as they provided favourable results. The plots of these unaligned profile sets are shown in Fig. 5.8.

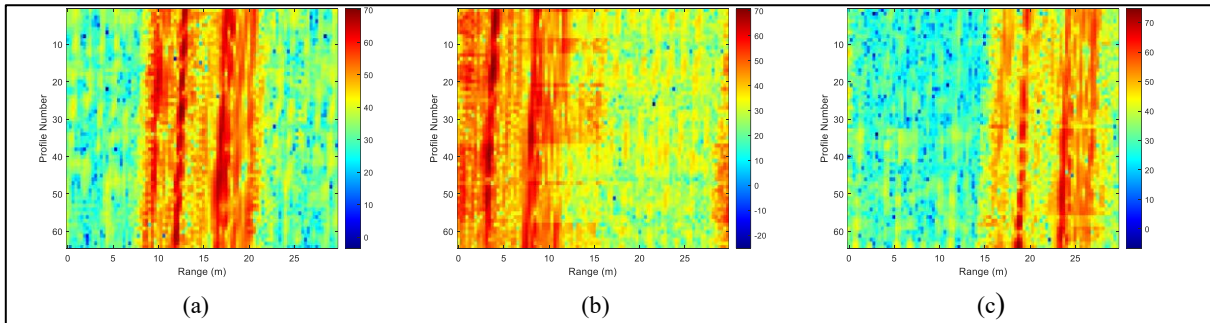


Figure 5.8 Subsets of the HRR profiles with the middle profile: (a)2464, (b)2970, (c)3827

The envelope correlation range alignment was applied to each of the three subsets of HRR profiles of the Zayaan vessel. The integer shifts each profile needs to undergo were calculated, and this is displayed in Fig. 5.9. The translation motion of the Zayaan was much slower than the Umoya Omusha vessel. For this reason, profiles in the Zayaan dataset are similar, and many profiles require the same number of shifts for alignment.

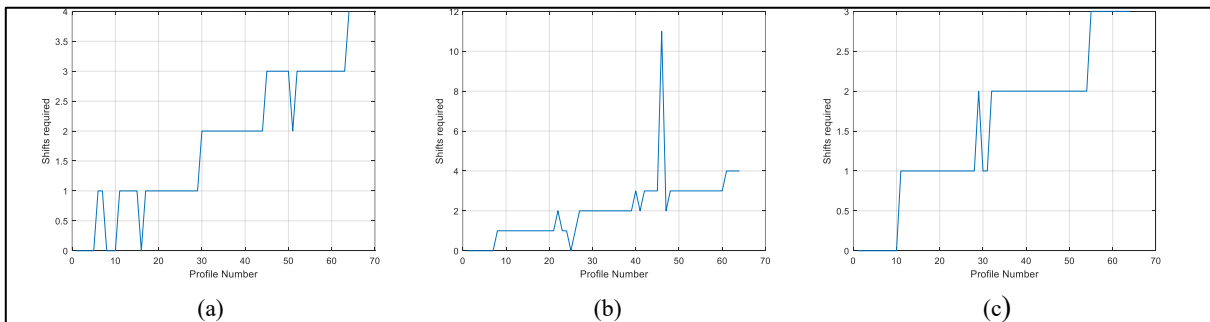


Figure 5.9 Number of shifts required per profile for middle profile: (a)2464, (b)2970, (c)3827

Fig. 5.10, shows the plots of the final range-aligned profiles. Alignment has occurred as is visually seen due to the vertical red lines indicating dominant scatterer alignment. Scatterer movement between range bins is lower than in the unaligned HRR profiles. The resulting unfocused ISAR image is shown in Fig. 5.11.

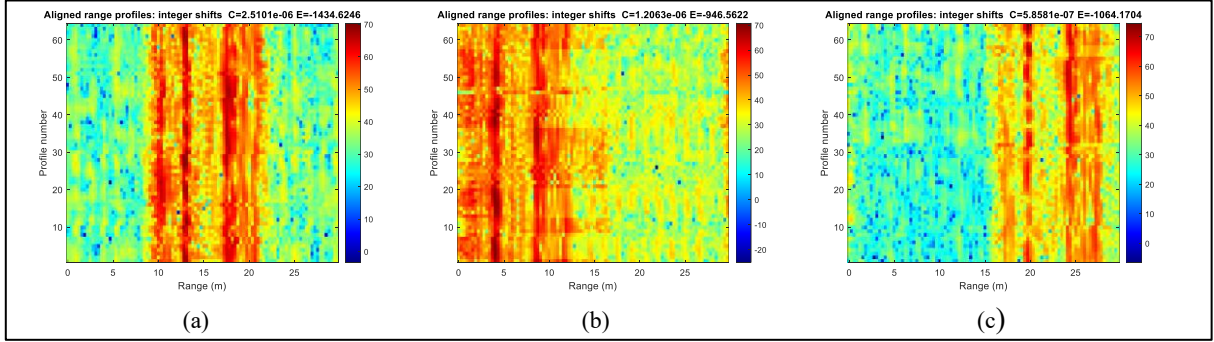


Figure 5.10 Aligned range profiles (integer shift) for middle profile: (a)2464, (b)2970, (c)3827

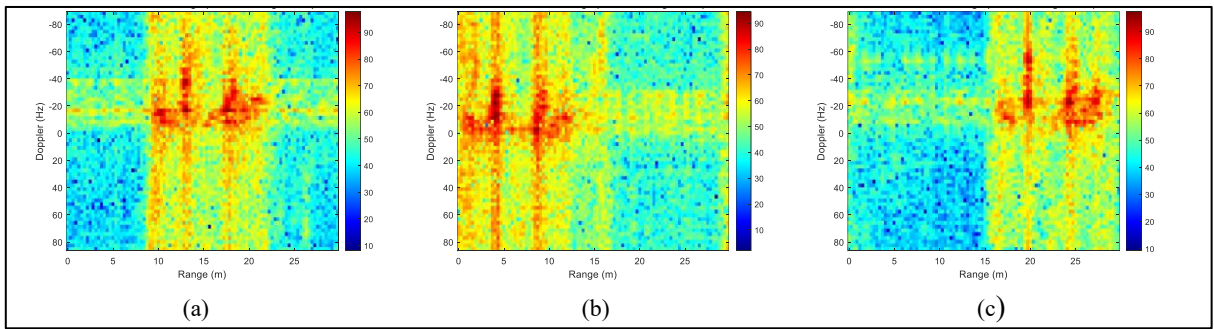


Figure 5.11 Unfocused ISAR image (with integer shift RA) for middle profile: (a)2464, (b)2970, (c)3827

5.1.2 Sub-integer Shift (Envelope Correlation) algorithm results

A high-level processing flow for the sub-integer shift range alignment is depicted in Fig. 5.12.

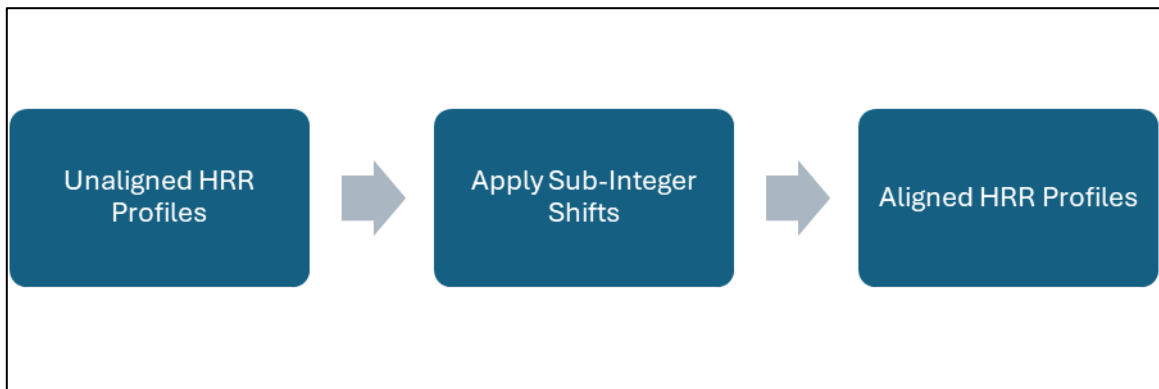


Figure 5.12 High-level processing steps for sub-integer shift range alignment

Phase shift vector

An HRR profile was shifted by a non-integer value by multiplying the FFT of an unaligned profile with a phase shift vector, and then the IFFT was applied to bring the signal back to the time domain. Equation 5.1 provides the formula for the phase shift vector. Keep in mind that a phase shift vector, which is used to implement a non-integer shift, is applied to one HRR profile. Since each profile needs a different non-integer bin shift, a distinct phase shift vector was required for each profile [5].

$$phase_shift_vector = e^{j2\pi s_l m/n} \quad (5.1)$$

Where:

- n is the number of range bins
- $m=0:1:(N-1)$
- N is the number of profiles,
- s_l is the non-integer delay for the l_{th} profile

Reason for fitting a low-order polynomial of order 2

A low-order polynomial was fitted to the integer shifts per profile determined by the earlier equivalent algorithms to estimate the non-integer bin shifts per HRR profile. A polynomial of order 2 was selected for this project since the vessel's translation motion is dominated by its velocity over CPI intervals between 0.5s and 1s.

Umoya Omusha

Fig. 5.13 displays the number of integer shifts each unaligned profile had to undergo. This is shown for all the corresponding middle profiles as well. The second-order polynomial is indicated by the red line. This creates the sub-integer shifts. For each middle profile, a negative gradient is expected given the shape of the integer shifts graph.

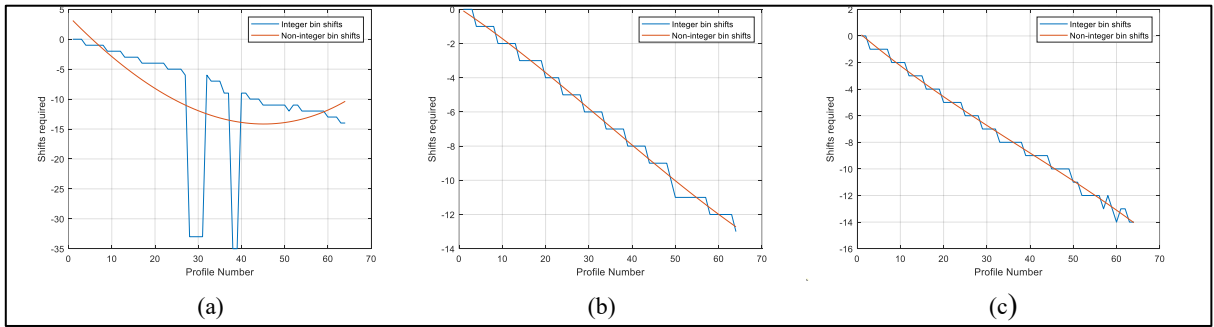


Figure 5.13 Number of shifts required per profile for middle profile: (a)180, (b)1010, (c)1384

The resulting aligned HRR plots are displayed in Fig. 5.14. Similarly to the integer shift algorithm, profile 1 was chosen as the reference profile. It is evident that here, there is better alignment than in the integer shift algorithm in Fig. 5.6. In Fig. 5.6 there was a greater scatterer migration than shown in Fig. 5.14. Also, due to using sub-integer shifts, there are no periodic jumps as was previously witnessed. In Fig. 5.14 (b), at approximately 11 m the dominant scatterer looks well-aligned. This is also seen in Fig. 5.14(c) at approximately 10m. These are clear visual indicators of improved alignment. In general, these HRR profiles look visually better. The contrast values of these plots are higher than their previously seen counterparts shown in Fig. 5.6. Moreover, their entropy values are mostly lower. This backs up the visual improvement. In Fig. 5.15, the unfocused ISAR images that follow are shown.

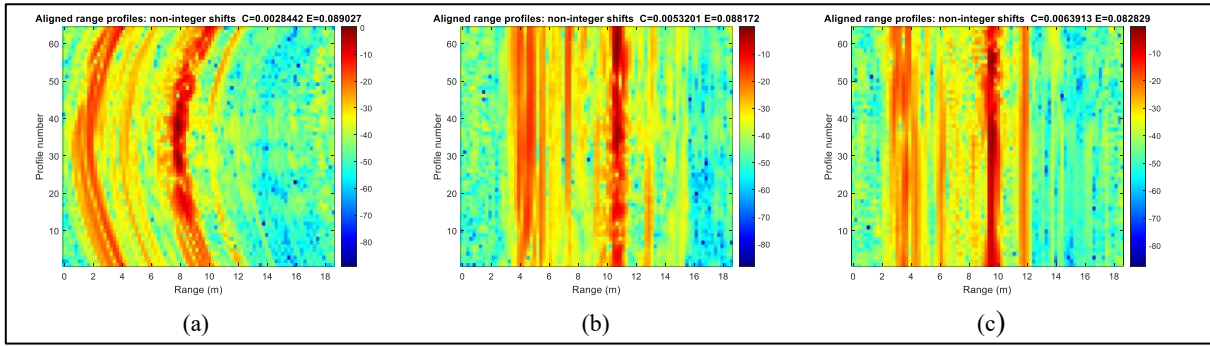


Figure 5.14 Aligned range profiles (sub-integer shift) for middle profile: (a)180, (b)1010, (c)1384

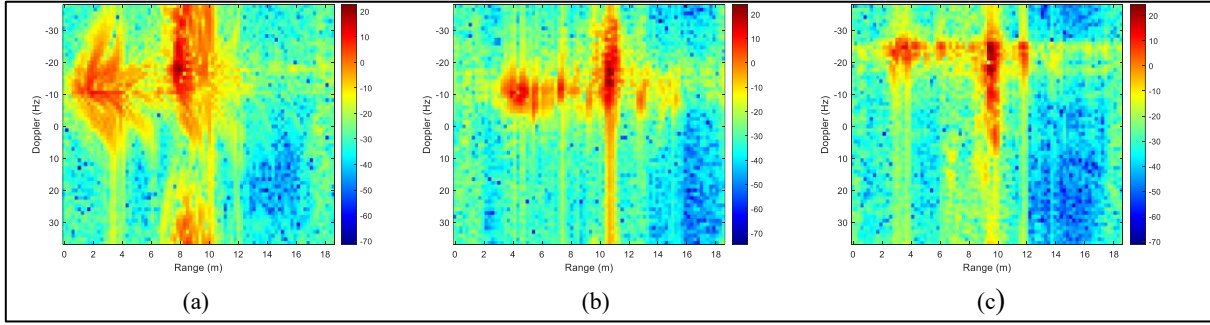


Figure 5.15 Unfocused ISAR image (with sub-integer shift RA) for middle profile: (a)180, (b)1010, (c)1384

Zayaan vessel

The results for the Zayaan Vessel are presented identically to the Umoya Vessel. In Fig. 5.16 it is apparent how the low-order polynomial fits the previously calculated integer shifts. Due to the shifts not being very staircase-like, a less linear fit is achieved. HRR profiles change from profile to profile, and the 1st profile makes a poor reference. This is one reason why a staircase function was not observed. However, the sub-integer shifts are still generated in this way. Once more, this is shown for all three subsets of HRR profiles.

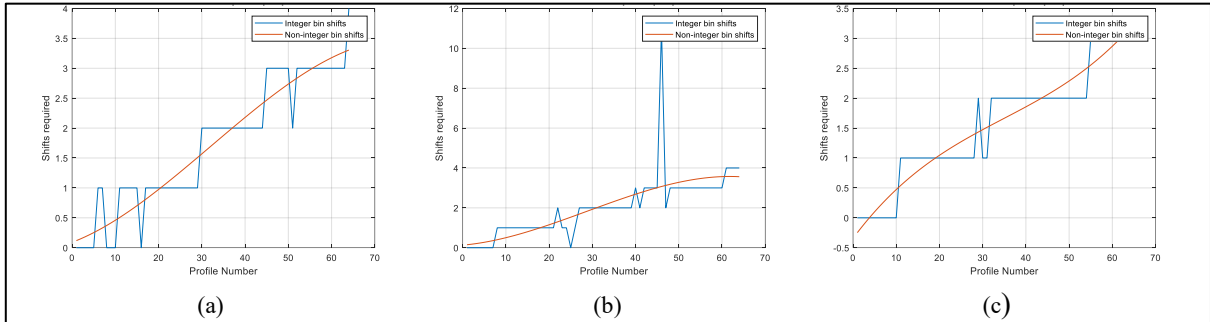


Figure 5.16 Number of shifts required per profile for middle profile: (a)2464, (b)2970, (c)3827

The resulting aligned HRR plots are displayed in Fig. 5.17. Similarly to the integer shift algorithm, profile 1 was chosen as the reference profile. It is evident that here, there is better alignment than in the integer shift algorithm in Fig. 5.10. In Fig. 5.10 there was a greater scatterer migration than can be seen in Fig. 5.17. Also, due to using sub-integer shifts, there are no periodic jumps as was previously witnessed. In Fig. 5.17 (b) at approximately 11 m, the dominant scatterer looks well-aligned. This is also seen in Fig. 5.17(c) at approximately 10m. These are clear visual indicators of improved alignment. In general, these HRR profiles look visually better. The contrast values of these plots are higher than their previously seen counterparts shown in Fig. 5.10. Moreover, their entropy values are mostly lower. This backs up the visual improvement. In Fig. 5.18, the unfocused ISAR images that follow are shown.

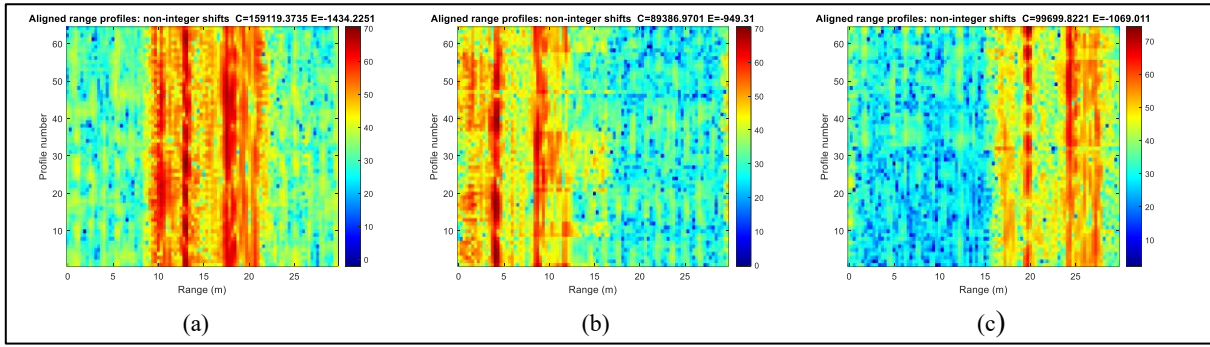


Figure 5.17 Aligned range profiles (sub-integer shift) for middle profile: (a)2464, (b)2970, (c)3827

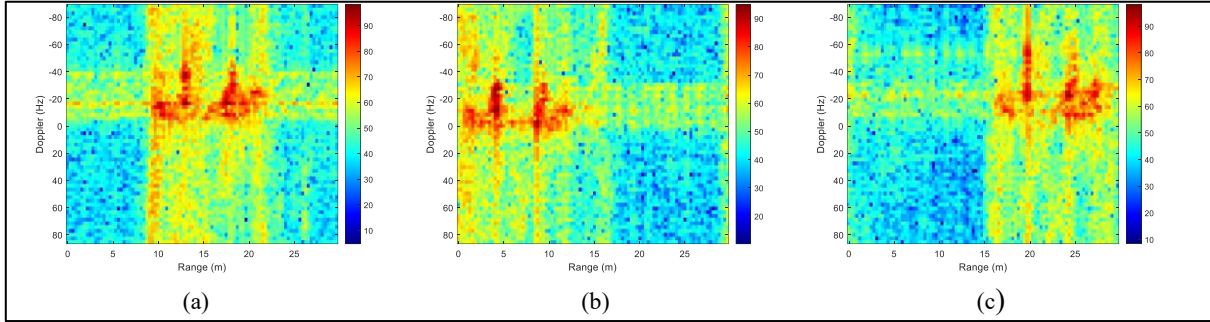


Figure 5.18 Unfocused ISAR image (with sub-integer shift RA) for middle profile: (a)2464, (b)2970, (c)3827

5.2 Combination of Range Alignment and Autofocus algorithms to find the optimal processor

Preceding the alignment, the final step was to perform autofocus on the aligned HRR profiles to correct for phase errors that remained from imperfect range alignment. This results in more focused images, and when the rotation motion of the vessel contains dominant pitch motion, the ISAR image may resemble the side view of the vessel. As previously mentioned, two autofocus algorithms were investigated. Based on the previous results, it is evident that the sub-integer shift envelope correlation range alignment algorithm produced more favourable results. For this reason, the autofocus algorithms were applied to the aligned profiles using the sub-integer shift envelope correlation algorithm to identify the better-performing autofocus technique.

5.2.1 Dominant Scatterer Autofocus

Firstly, the dominant scatterer autofocus algorithm was investigated. The theory and method were discussed in Chapter 2 and Chapter 3, so only the results are displayed.

Umoya Omusha Vessel

In Fig.5.19, the final ISAR images for the three subsets of HRR profiles of the Umoya Omusha vessel are shown. The image contrast is displayed, and the correlation between quantitative and qualitative measures of success is apparent. Fig. 5.19(a) appears to be the worst image from a visual point of view and has the worst contrast value, whereas Fig. 5.19(c) has the most focused image and the highest contrast value. The results are favourable as Fig. 5.19 (b) and (c) resemble the side-view of the vessel, which was shown in Chapter 3. The single long mast can be easily identified.

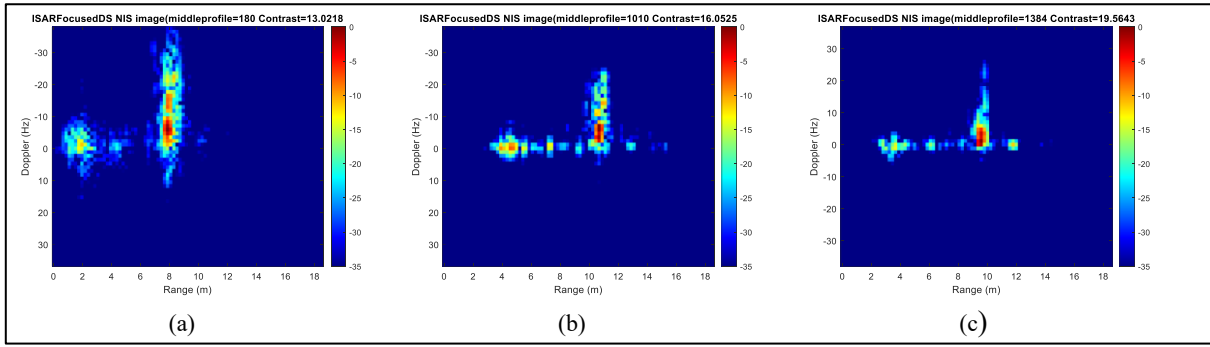


Figure 5.19 ISAR-focused image for middle profiles: (a)180, (b)1010, (c)1384 with sub-integer shift Range Alignment and Dominant Scatterer Autofocus

Zayaan Vessel

In Fig. 5.20 the final ISAR images for the three subsets of HRR profiles of the Zayaan vessel are shown. The image contrast is displayed, and the correlation between quantitative and qualitative measures of success is apparent. Fig. 5.20(a) appears to be the best image from a visual point of view and has the best contrast value, whereas Fig. 5.20(b) has the least focused image and the lowest contrast value. The results are favourable as Fig. 5.20(a) resembles the side-view of the vessel, which was shown in Chapter 3. The two masts of the vessel can be identified.

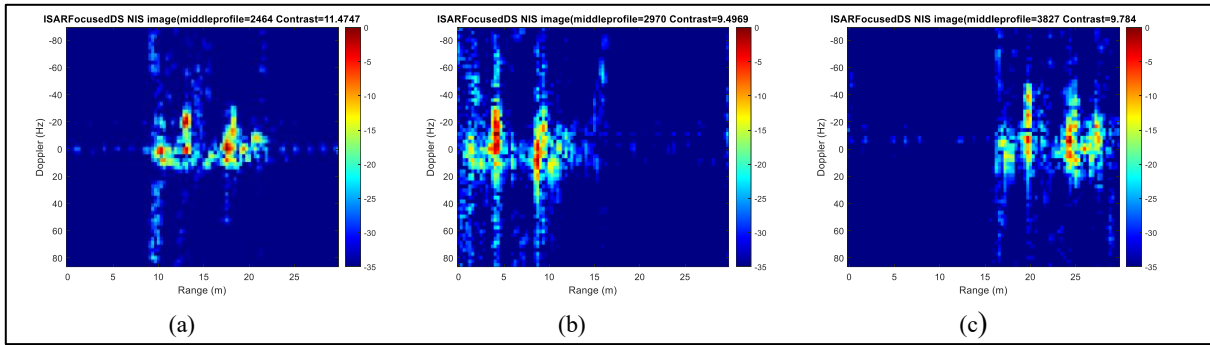


Figure 5.20 ISAR-focused image for middle profiles: (a)2464, (b)2970, (c)3827 with sub-integer shift Range Alignment and Dominant Scatterer Autofocus

5.2.2 Weighted multiple scatterer (Yuan) algorithm

Lastly, the results of the weighted MSA are presented. With the theory already being discussed in Chapter 2 and Chapter 3, only the resulting ISAR images are displayed.

Umoya Omusha Vessel

In Fig. 5.21 the final ISAR images for the different middle profiles of the Umoya Omusha vessel are shown after the weighted multiple scatterer autofocus technique was implemented. As with the previous results, the image contrast is displayed, and the correlation between quantitative and qualitative measures of success is apparent. The images with a higher contrast are also more focused. Fig. 5.21(c) is the best image visually, and it possesses the highest contrast. Contrary Fig. 5.21(a) is the least visually appealing image, and unsurprisingly, it has the lowest contrast value. The results are favourable as Fig. 5.21(b) and Fig. 5.21(C) both resemble the side-view of the vessel.

Comparing these results of the weighted MSA to those of the dominant scatter autofocus algorithm, one algorithm is not significantly better than the other. Although for the middle profiles of 180 and 1010, the results are more favourable qualitatively and quantitatively for the dominant scatterer algorithm, this is not the case for the middle profile of 1384. In this case, although it is visually difficult to distinguish between Fig. 5.19(c) and Fig. 5.21(c), the latter has a better image contrast, making it the best image produced across both algorithms.

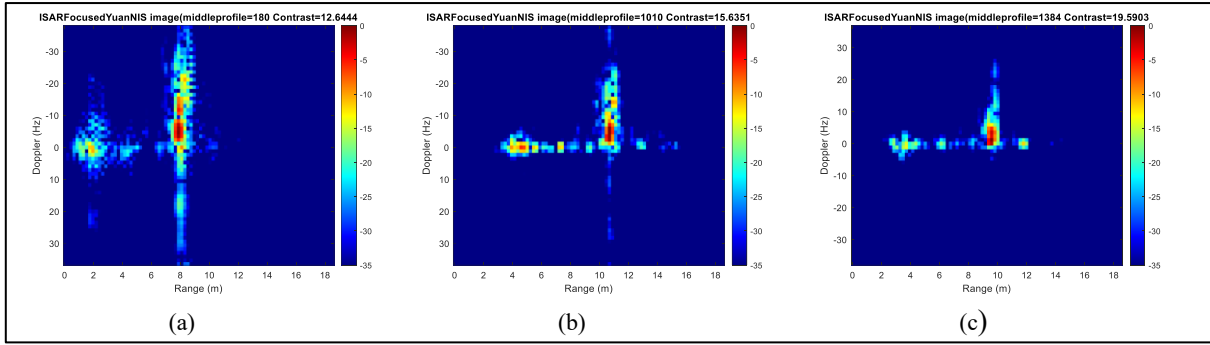


Figure 5.21 ISAR-focused image for middle profiles: (a)180, (b)1010, (c)1384 with sub-integer shift Range Alignment and Weighted Multiple Scatterer Autofocus

Zayaan Vessel

In Fig.5.22, the final ISAR images for the different middle profiles of the Zayaan vessel are shown. As before these are the images after the weighted multiple scatterer autofocus technique was implemented. Once more, the image contrast is displayed, and the correlation between quantitative and qualitative measures of success is noticeable. The clearer images, which more accurately resemble the vessel, possess higher contrast values. However, simply having a higher contrast does not necessarily mean the image is better for target classification. Fig. 5.22(a) has a slightly lower contrast value than Fig. 5.22(b), however, it is a better visual image due to the large Doppler spread found at ~4m on the latter figure. Fig. 22(c), on the other hand, has a much lower contrast compared to the previous two images, and it shows in its inferior image quality. Fig. 5.22(a) provides a strong argument for the success of this algorithm. When comparing these results with the results from the dominant scatter autofocus algorithm, once more, it is difficult to conclude that one algorithm performs significantly better than the other. The images in Fig. 5.20 are very similar to those in Fig. 5.22. For the middle profiles of 2464 and 3827, the contrast values are slightly higher in Fig. 5.20(a) and Fig. 5.20(c). However, with regards to the middle profile of 2970, Fig. 5.22(b) possesses a significantly higher value than Fig. 5.20(b). The best-produced image for this dataset, according to both quantitative and qualitative measures, remains Fig. 5.20(a).

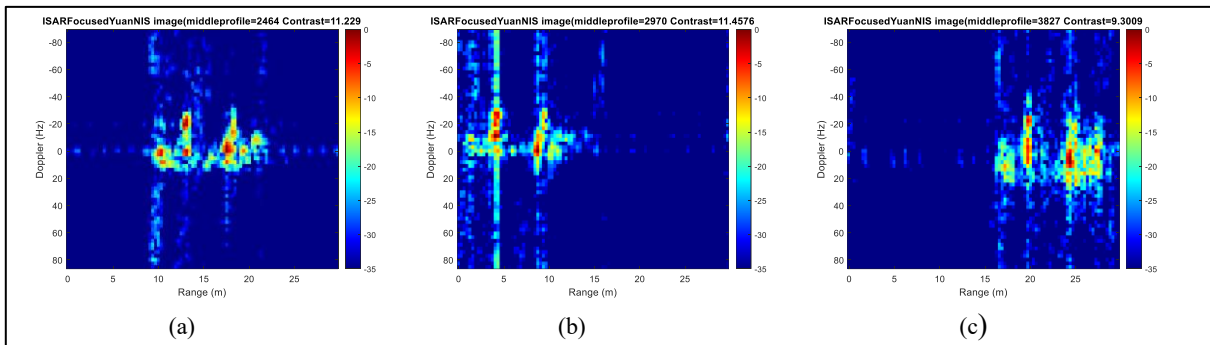


Figure 5.22 ISAR-focused image for middle profiles: (a)2464, (b)2970, (c)3827 with sub-integer shift Range Alignment and Weighted Multiple Scatterer Autofocus

Fig. 5.20(a) is the image with the highest contrast value (11.4747) for the Zayaan vessel, whereas Fig. 5.21(c) is the image with the highest contrast value (19.5903) for the Umoya vessel. This makes Fig. 5.21(c) the image with the highest contrast value across both datasets, in combination with it being a visually appealing image. A summary of the results is given in Table 5.1.

Table 5.1 Summary of the Contrast values obtained for both vessels

Contrast values as per Autofocus Method	Vessel					
	Umoya			Zayaan		
	Middle profile: 180	Middle profile: 1010	Middle profile: 1384	Middle profile: 2464	Middle profile: 2970	Middle profile: 3827
Dominant Scatterer Autofocus Contrast	13.0218	16.0525	19.5643	11.4747	9.4969	9.784
Weighted Multiple Scatterer Autofocus Contrast	12.6444	15.6351	19.5903	11.229	11.4576	9.3009

5.3 Conclusion of translation motion results

The sub-integer range alignment algorithm offered superior performance in alignment than the integer envelop correlation range alignment algorithm. This was apparent as qualitatively, the profiles were visually more aligned. This was also justified by the increases in contrast and the decrease in entropy for both datasets. The sub-integer shift algorithm produced better images based on the quality measures, and therefore, the preceding algorithms used it as the first step. The sub-integer offers better range alignment universally as it accounts for fractional shifts, improving accuracy.

Next, the dominant scatterer technique, followed by the sub-integer shift range alignment algorithm, produced favourable images. The same can be said for the MSA as well. In comparison to each other, the results could not provide a definitive answer for which algorithm was better. This was due to each algorithm performing differently depending on which dataset was used and which middle profile was used. The weighted MSA was selected for the ITWSP as it is more thorough than the dominant scatterer algorithm, whilst still being efficient. It is more consistent across more middle profiles when chosen at random, and it produced the image with the highest contrast value across both datasets, thus, it is chosen for the ITWSP.

As was seen, the middle profile plays an important role in determining the quality of the final image produced. Therefore, in the following chapter, techniques to optimise this middle profile, as well as the window length of the profiles analysed, are investigated to create an ideal ISAR image.

6. Optimum Image Interval Techniques Results

The development of an ITWSP was the essential objective of this dissertation. The primary goal of the processor was to identify ISAR images that contain essential information for classification, without needing large computing power. In Chapter 5, it was evident that certain intervals of the data produced better images that resembled the side-view projection of the sea vessel. Therefore, finding suitable imaging intervals within a data recording with optimal lengths has the potential to generate better ISAR images for classification purposes.

6.1 Maximum contrast-based automatic time window selection results

Assuming a fixed processing interval, the factor that most influenced the quality of the images in Chapter 5 was the middle profile of the interval. Therefore, optimising with respect to the middle profile would be beneficial in the search for high-quality images. Another factor that would influence the quality of the image is the duration of the processing interval, which is commonly referred to as the CPTWL. Thus, an optimisation of the CPTWL was also investigated. This forms the basis for the maximum contrast-based automatic time window. The quantitative metric used to assess the optimisation is the image contrast of the multiple ISAR images. The method of the algorithm is given in the steps below:

Step 1: A suitable CPTWL is estimated.

In particular, the radar PRF and the target motion velocity are two parameters to take into account to set the initial value, $\Delta\tau^{(in)}$.

Step 2: Maximization of the contrast with respect to τ for a given guess, $\Delta\tau = \Delta\tau^{(in)}$ (let τ_{opt} be the solution).

Step 3: Optimization with respect to $\Delta\tau$ with $\tau = \tau_{opt}$ which gives $\Delta\tau_{opt}$.

The middle profile is now acquired so now the best window is found, by means of a trial-and-error method as follows:

- The IC is recalculated after the window length is increased by $2n$ samples until it no longer increases. The algorithm's rate of convergence is impacted by the value of n . Once more, the radar PRF and the target motion velocity determine this value. The values 4, 5, and 6 are some common values chosen for n .
- The step is repeated where the window length is increased by $2(n - k)$ samples, for $k = 1, \dots, n$.
- In the case that the image contrast decreases on the first iteration:
 - a) the window length is then decreased by $2n$ samples,
 - b) The step is repeated where the window length is decreased by $2(n-k)$ samples, for $k=1, \dots, n$.

6.1.1 *Umoya Omusha Vessel*

The first radar data recording considered was the measured data of the Umoya Omusha vessel. Using the same dataset as in Chapter 5 and continuing with the results of the envelope correlation range alignment algorithm, the following results are produced.

i. Central instant selection or middle profile optimisation

The first step of the MC-ATWS algorithm was to optimise the middle profile. This was done by selecting multiple middle profiles between the first profile and the last profile, ensuring an overlap of 50% between profiles. Firstly, a suitable CPTWL was established based on the PRF. This initial value was chosen to be 32 profiles, as discussed in Chapter 3. The middle profiles that corresponded to the local peaks of the image contrast values were chosen to be the final subset of optimal middle profiles. The number of local peaks chosen for this subset was based on the MATLAB “findpeaks” function. In this function, a minimum peak height was defined as well as a minimum peak prominence. The minimum peak height was set to be the mean value of the image contrast values found in the initial step. The minimum peak prominence for this dataset was set to 4. This resulted in the 13 optimal middle profiles and subsequently, 13 optimised ISAR images, which are displayed in Fig. 6.1(a)-(m).

It is evident from Fig. 6.1 that the selection of the middle profile affects the quality of the ISAR image produced. This reinforces the conclusion made in Chapter 5. Fig. 6.1(a),(d),(h) display ISAR images resembling the side-view optical image of the Umosha vessel, as the single mast is clearly visible. These images also contain high contrast values relative to the others. Fig. 6.1(e),(g),(k),(l) are also good quality ISAR images according to their high contrast values and their resemblance to the optical image. In these intervals, the yacht’s mast moved away from the radar, and this resulted in negative Doppler frequencies being observed in the ISAR image. Fig. 6.1(b),(c),(f),(i),(j) are visually lower quality images, since the mast is not clearly visible in the ISAR image, even though some of them possess relatively high image contrasts. This further emphasises the idea that a quantitative measure is not sufficient to assess the quality of an ISAR image for classification. Furthermore, other ISAR images containing a single mast may have been overlooked by the algorithm when it does not correspond to the local peak in the image contrast values.

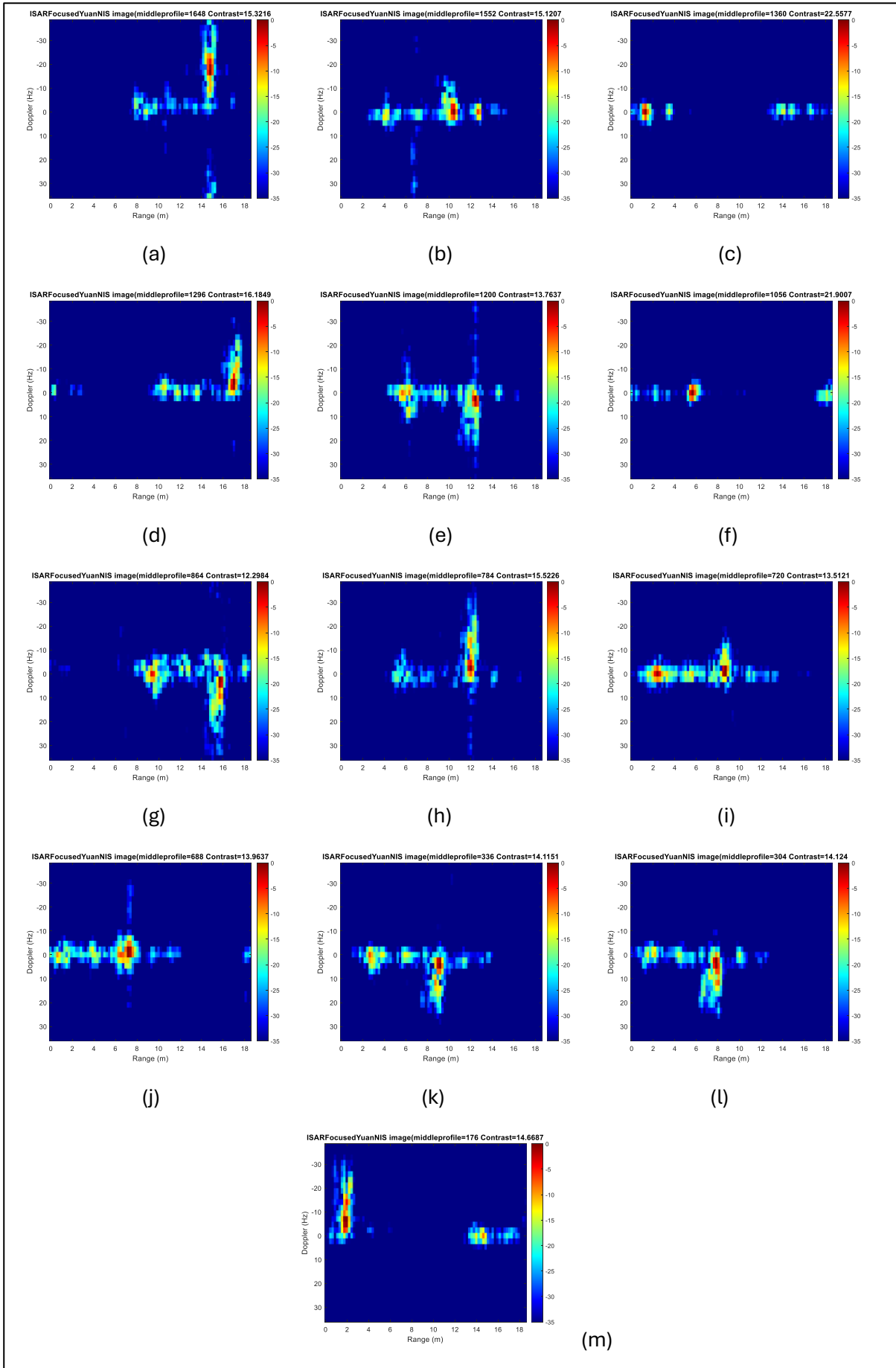


Figure 6.1 ISAR images after the middle profile optimisation

ii. *Window-length optimisation*

With the optimum middle profile step completed, a set of 13 ISAR images was produced. All these images had a window length of 32 profiles. The next step was to optimise the window length for each middle profile so that the optimum CPTWL resulted in the ISAR image with the highest contrast. In some cases, it was found that the initial CPI of 32 was already the optimum CPTWL, as shown in Fig. 6.2 (d),(g). However, in Fig. 6.2 (a)-(c),(e),(f),(h)-(m) new optimal CPTWLs were found. In all those cases, the image contrast increased.

Fig. 6.2 consists of 13 subfigures, each displaying a range-Doppler representation with a colour scale indicating intensity values. The key quantitative and qualitative factors to consider were the image contrast value and visual appearance, respectively. In subfigures with higher contrast, there are sharper distinctions between the bright areas and the background.

In subfigures with lower contrast, the intensity changes are more subtle, making features less distinguishable. Some subfigures exhibit clear, well-defined structures, while others appear more diffused or fragmented.

Subfigures with high-contrast features tend to highlight specific target structures, whereas lower-contrast ones may obscure details.

Fig. 6.2 (c),(f) have the highest image contrast values, however, those images do not contain discriminative information for classification since the single mast of the yacht cannot be observed. In comparison, Fig. 6.2 (g),(i), which contain some of the lower image contrast values, produce better ISAR images for classification purposes. Fig. 6.2 (a),(e),(h) have moderate image contrast values and produce good visual ISAR images, which more accurately resemble the optical side-view image of the vessel. They have clear, well-defined intensity regions. The bright spots stand out against the background, making the structures more discernible. The contrast between the intensity levels is not as sharp as in the high-contrast cases, but distinguishable features such as the singular mast are more apparent.

The brightness and intensity distribution vary across the subfigures, indicating the different effects of the processing technique, based on the CPI and middle profile used. Some images show multiple bright clusters, suggesting more complex target structures, while others have a single dominant bright region exhibiting structures like masts. The contrast and clarity of each subfigure vary, affecting how well target features can be observed. In general, the image contrast of an ISAR image is not sufficient to represent the quality of the image for classification, and qualitative measures should also be used when performing operator-based classification.

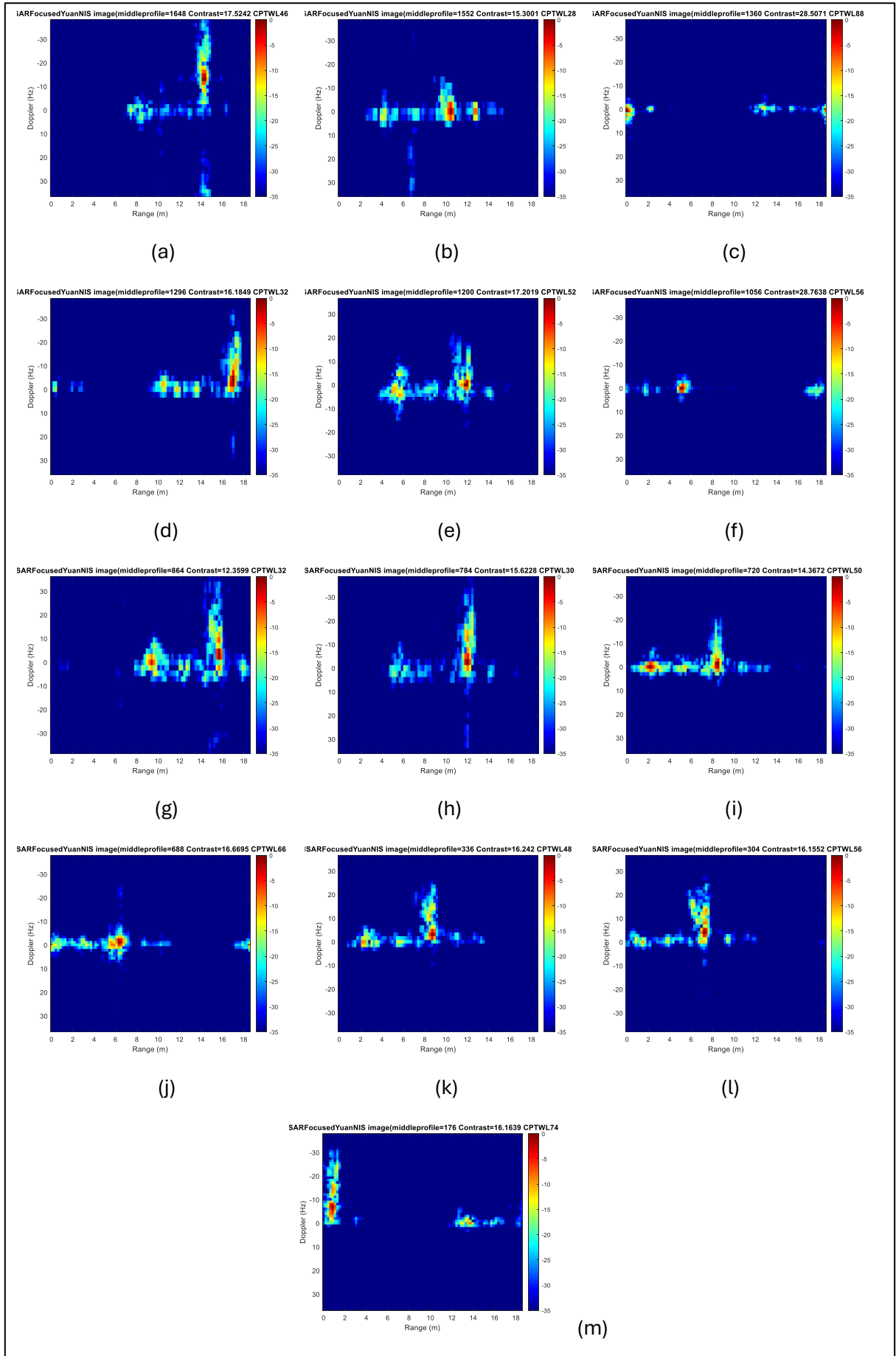


Figure 6.2 ISAR images after window-length optimisation

6.1.2 Zayaan Vessel

The next data recording that was analysed was of the Zayaan vessel. The following outcomes are obtained by using the envelope correlation range alignment technique on the same dataset as in Chapter 5.

i. Middle profile optimisation

Like the process described in Section 6.1.1 for the Umoya vessel, the first step of the algorithm applied to the recording of the Zayaan vessel involved optimising the middle profile. This was once again done by selecting multiple middle profiles between the first and last profiles, ensuring a 50% overlap. As stated earlier, an appropriate initial CPTWL value was set to 64 profiles. The subset was then refined based on image contrast values, selecting the middle profiles with the highest contrast. Just like before, the number of profiles chosen for this subset was determined using MATLAB's "findpeaks" function and initialising two key input parameters: the minimum peak height and the peak prominence. The minimum peak height was set to the mean of the image contrast values from the initial step, and the peak prominence was set to a value of 8. This resulted, yet again, in 13 optimal middle profiles, leading to 13 optimised ISAR images, which are shown in Fig. 6.3(a)-(m). The number of resulting images is due to the peak prominence set, as this filters out the images. Therefore, the peak prominence was carefully selected to imitate the same number of results as with the Umoya vessel, to make the results more comparable. As previously noted, these images demonstrate how the middle profile selection impacts the ISAR image quality, further reinforcing the conclusion drawn in Chapter 5.

The ISAR images in Fig. 6.3(b), (d), and (f) clearly show the Zayaan vessel's two masts, which closely resemble the side-view optical image of the fishing vessel. In Fig. 6.3(c), even though the front and rear of the vessel appear at opposite ends of the range axis due to profile wrapping, the image possesses discriminant information useful for classification. While some images in Fig. 6.3(a), (e), and (g)–(l) have relatively high contrast, their overall visual quality for operator-based classification is lower. This highlights the limitation of relying solely on a quantitative metric to assess ISAR image quality. As with the Umosha vessel, some high-quality images with lower contrast values may have been missed during the first step of the algorithm, since they didn't align with the local peak of the image contrast values.

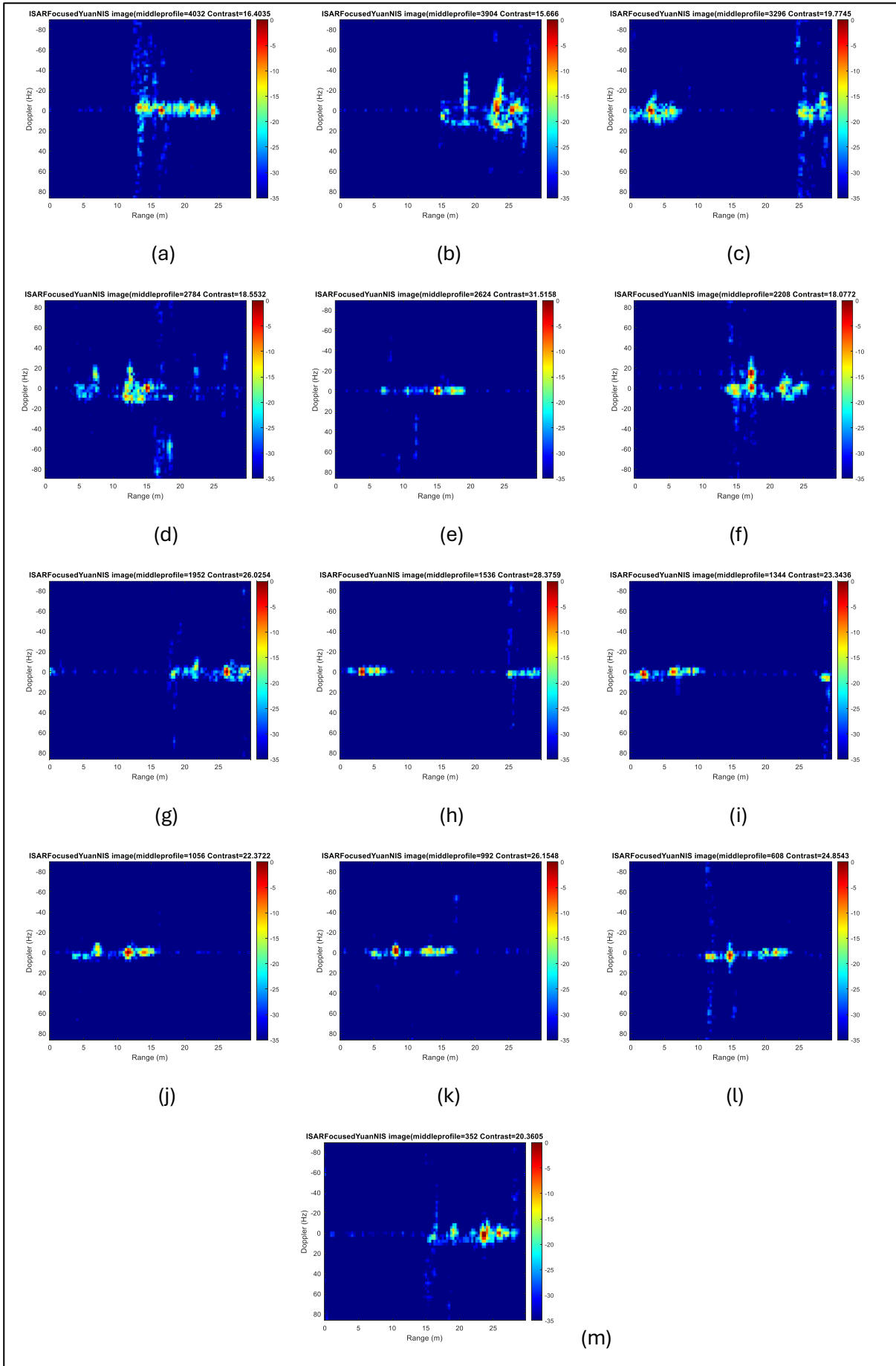


Figure 6.3 ISAR images after the middle profile optimisation

ii. *Window-length optimisation*

As shown with the data recording of the Umoya vessel, after the optimum middle profile step was completed for the data recording of the Zayaan vessel, a total of 13 ISAR images were generated. Again, the next step involved optimising the CPTWL for each middle profile found in the first step. Consequently, the CPI was systematically adjusted until the ISAR image with the highest contrast value was achieved. In some instances, the initial CPTWL of 64 profiles had already produced the ISAR image with the highest image contrast, as seen in Fig. 6.4(a),(b),(c). However, in other cases, such as Fig. 6.4(d)-(m), a new optimal CPTWL was identified. In all these instances, the image contrast of the ISAR images generated after optimising the CPTWL showed a noticeable improvement.

Similarly to Fig. 6.2, Fig. 6.4 includes 13 subfigures, each showing a range-Doppler representation with a colour scale to indicate intensity. Once again, the quantitative and qualitative metrics used to assess the quality of the ISAR images consisted of computing the image contrast and observing the visual clarity of the ISAR images for operator-based classification. High-contrast images, as previously discussed, make bright areas stand out sharply against the background, making details easier to see. On the other hand, lower-contrast images have more gradual intensity changes, which can make features harder to distinguish. Like before, some subfigures clearly show well-defined structures, while others look more blurred or fragmented. As we've seen, higher contrast helps bring out important details, while lower contrast can make them less noticeable.

Although Fig. 6.4 (e) and (h) have the maximum contrast levels, they do not have sufficient Doppler information to aid with operator-based classification. Comparatively, some of the ISAR images with discriminative information for classification are shown in Fig. 6.4 (b), (f), which have some of the lower image contrast levels, and Fig. 6.4 (m), (d) had moderate image contrast values. They more closely resemble the side-view of the vessel. Their intensity zones are distinct and easily observable. The structures of the vessel correspond to the bright solid pixels that contrast with the background. Though recognisable elements like the unique mast are more noticeable, the difference between the intensity levels is not as clear as it is in the high-contrast examples.

As previously mentioned, the brightness and intensity distribution vary across the subfigures, reflecting how the processing technique, based on the chosen CPTWL and middle profile, impacts the final image. This analysis simply reinforces that idea. Some images display multiple bright clusters, suggesting more complex target structures, while others feature a single dominant bright region, often representing structures like masts. As discussed before, contrast and visual clarity influence how well target features can be identified. Generally, contrast alone is not a reliable metric to determine the quality of an ISAR image for operator-based classification.

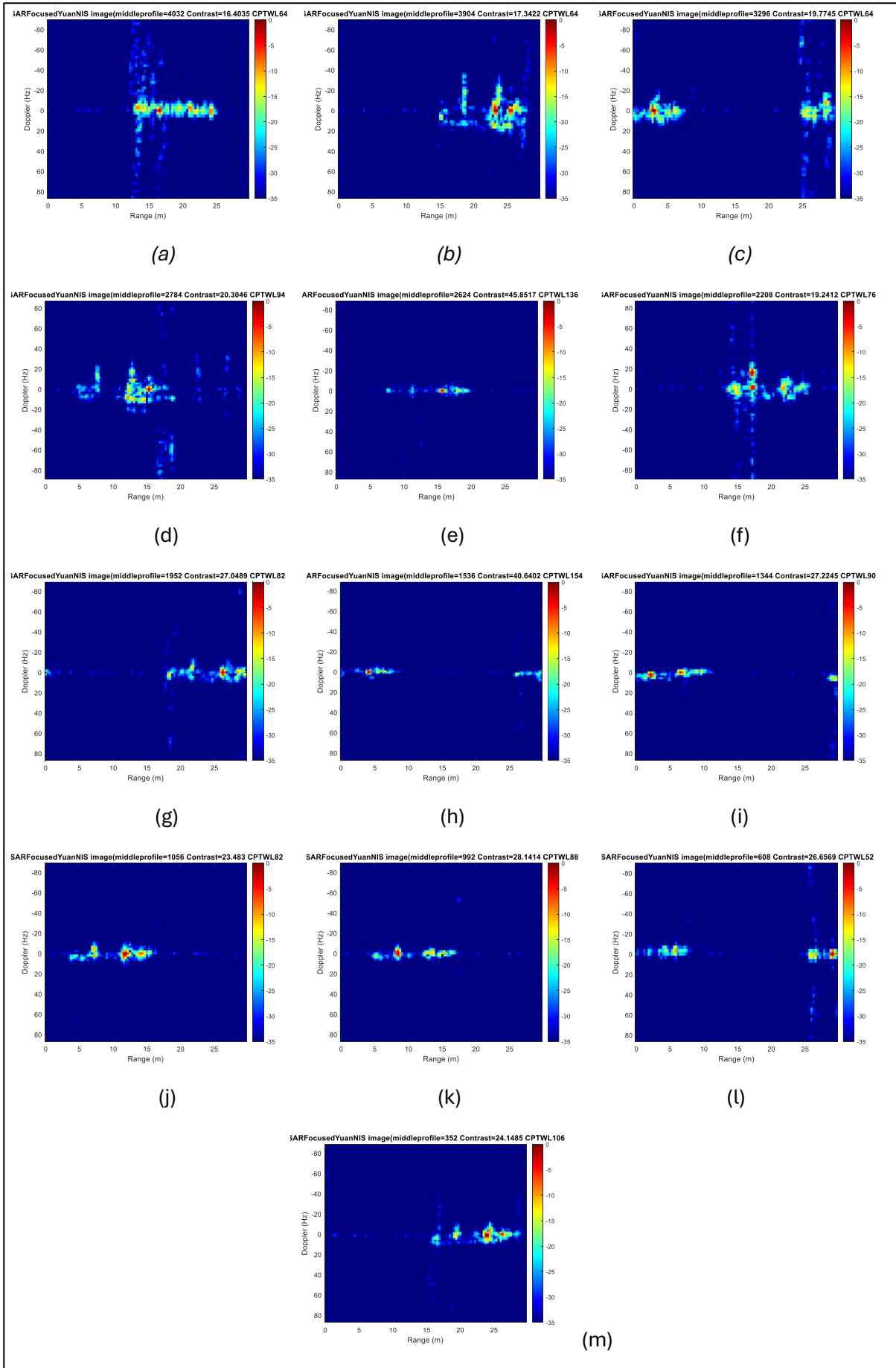


Figure 6.4 ISAR images after window-length optimisation

6.2 Optimal CPI Selection based on Image Contrast optimisation and Doppler Spread

In this section, the algorithm proposed by Cataldo and Martorella in [12] was applied to the measured radar data of both the Umoya Omusha vessel and the Zayyan vessel. Intermediate results of the algorithm are presented through the 3 main steps of the algorithm, which are range gating, central instant selection, and optimal time window length selection. The key variable values that were set are also discussed.

The method is split up into parts A, B, and C for simplicity. Section C is a function required by B. The sections are described below:

Part A: The optimum centre profiles are obtained, $\hat{t}_{opt(1 \times N_c)}$.

Once the Spectrogram is calculated using the equations described in Chapter 2.9, the Doppler spread for each column of S from Equation 2.30 is calculated. This is done as follows:

- The mean of each column is calculated.
- The standard deviation of each column is calculated.
- The threshold described by $\lambda_i = \mu_i + k_{spec} \cdot \sigma_i$ is calculated.
- The Doppler spread described by Equation 2.33 is calculated.
- The local maxima in the DS curve is found, $\hat{t}_{opt}$.

Part B: For each optimum centre profile $\hat{t}_{opt,i}$, an optimum CPTWL $T_{opt,i}$ is obtained.

- Range alignment and autofocus are applied to the HRR profiles.
- The corresponding ISAR images are generated.
- The Doppler occupation is calculated as follows:
 - The Doppler profile is obtained
 - The Doppler spread is computed (This is derived from the function in **Part C**)
 - $T_{opt,i}$ is given by the T_i within the range described by Equation 2.34 and where the Image contrast is maximised.

Part C: An accurate Doppler spread of the ISAR image is calculated.

- The Doppler profile is obtained.
- The optimum threshold is determined:
 - Threshold candidates are defined.
 - For each candidate, the Doppler spread is computed.
- The Doppler spread curve is fitted with a hyperbolic curve:
 - The vertex of the hyperbola is obtained.
 - The optimum threshold is obtained, $\lambda_{DS,opt}$.
 - The DS is calculated.

6.2.1 Umoya Omusha Vessel

In the first step of the algorithm, the optimum centre profiles are obtained. This begins with the development of the spectrogram as shown in Fig. 6.5, using the equations from Chapter 2.9. An initial CPTWL of 0.8 seconds was used based on the repetition frequency of 80 Hz and the CPI of 64 profiles. Furthermore, a 50% overlap between successive frames was used. With the spectrogram now present, the Doppler Spread trend could be calculated by using a $k_{spec} = 1$ for the threshold described by $\lambda_i = \mu_i + k_{spec} \cdot \sigma_i$. The Doppler

Spread is shown in Fig. 6.6. The local maxima in the Doppler Spread curve are the optimum centre profiles. The optimum centre profiles found are summarised in Table 6.1.

Table 6.1 Optimal centre profiles obtained

Optimum Centre Profile							
96	256	544	1120	1280	1440	1536	1664

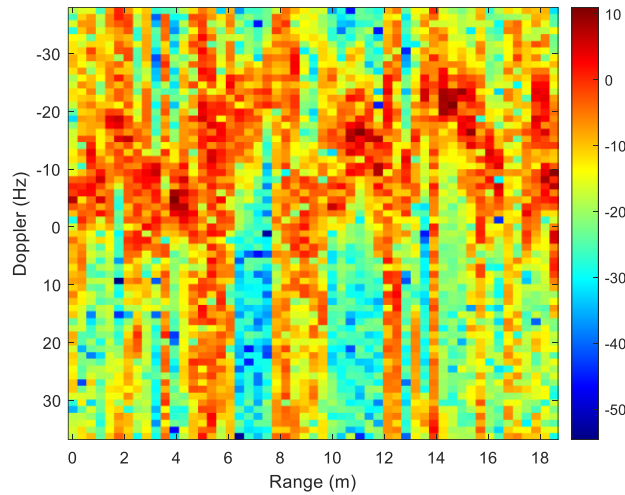


Figure 6.5 Spectrogram produced

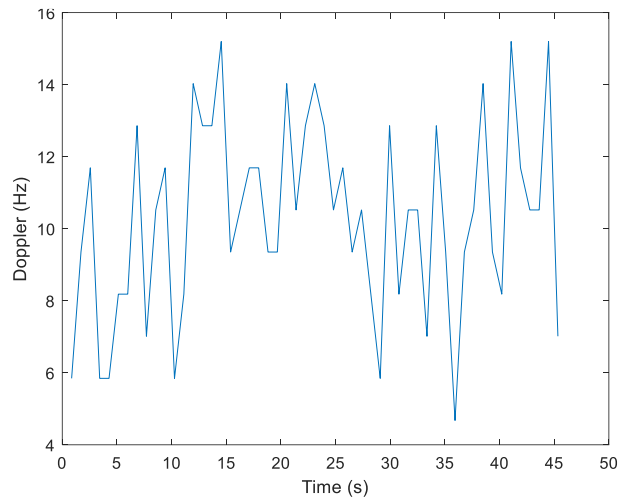


Figure 6.6 Doppler spread plot

Next, for each optimum centre profile, an optimum CPTWL was found. A set of candidate CPTWL was defined as $T=[0.1 \ 0.2 \ \dots \ 0.8 \ \dots \ 1.4 \ 1.5]$. After applying range alignment and autofocus, an ISAR image for each value in T was generated. Subsequently, the Doppler spread was calculated. This required calculating an accurate Doppler spread of the ISAR images. To calculate the Doppler spread the optimum threshold needed to be determined. A set of threshold candidates, $\lambda_{DS} = [\lambda_{DS1} \ \lambda_{DS2} \ \dots \ \lambda_{DSi} \ \dots \ \lambda_{DSN_\lambda}]$, were defined, and for each candidate, the Doppler spread was calculated. N_λ was set to 10. This Doppler spread curve was now fitted with a hyperbolic curve. After normalisation, the optimum threshold was obtained, and the Doppler spread was calculated. The optimum CPTWL for each candidate in T was given by the value which both maximised the contrast and fell within the Doppler Spread Range. The range defined by Equation 2.41, had a $k_{DS} = 0.1$. The optimum CPTWL for each optimum centre profile is given in Table 6.2.

Table 6.2 Optimal CPTWL values for each optimal centre profile

Centre Profile	Optimal values							
	96	256	544	1120	1280	1440	1536	1664
CPTWL	1.4	1.5	0.2	0.8	0.8	1.2	0.3	1

The final ISAR images, along with the plots generated in the process of forming them, are displayed in Fig. 6.7 – Fig. 6.14. Fig. 6.7(a) is the ISAR image generated for the optimum centre profile of 96. The optimal CPTWL was 1.4 seconds. The image had a contrast value of 12.24. In Fig. 6.7(b), the Doppler spread curve is depicted, with its corresponding fitted hyperbola. The image contrast for the candidate CPTWL values is shown in the plot of Fig. 6.7(d). This is projected onto the Doppler Spread plot in Fig. 6.7(c), which depicts the specified Doppler spread range. From this plot, it can be observed that the candidate of 1.4 seconds, which possessed the maximum contrast of 12.24, had a Doppler spread that satisfied the Doppler spread range criteria. The overall ISAR image does not look visually appealing, however, this could be improved by using a circular shift on the HRR profiles and by flipping the plot across the range axis.

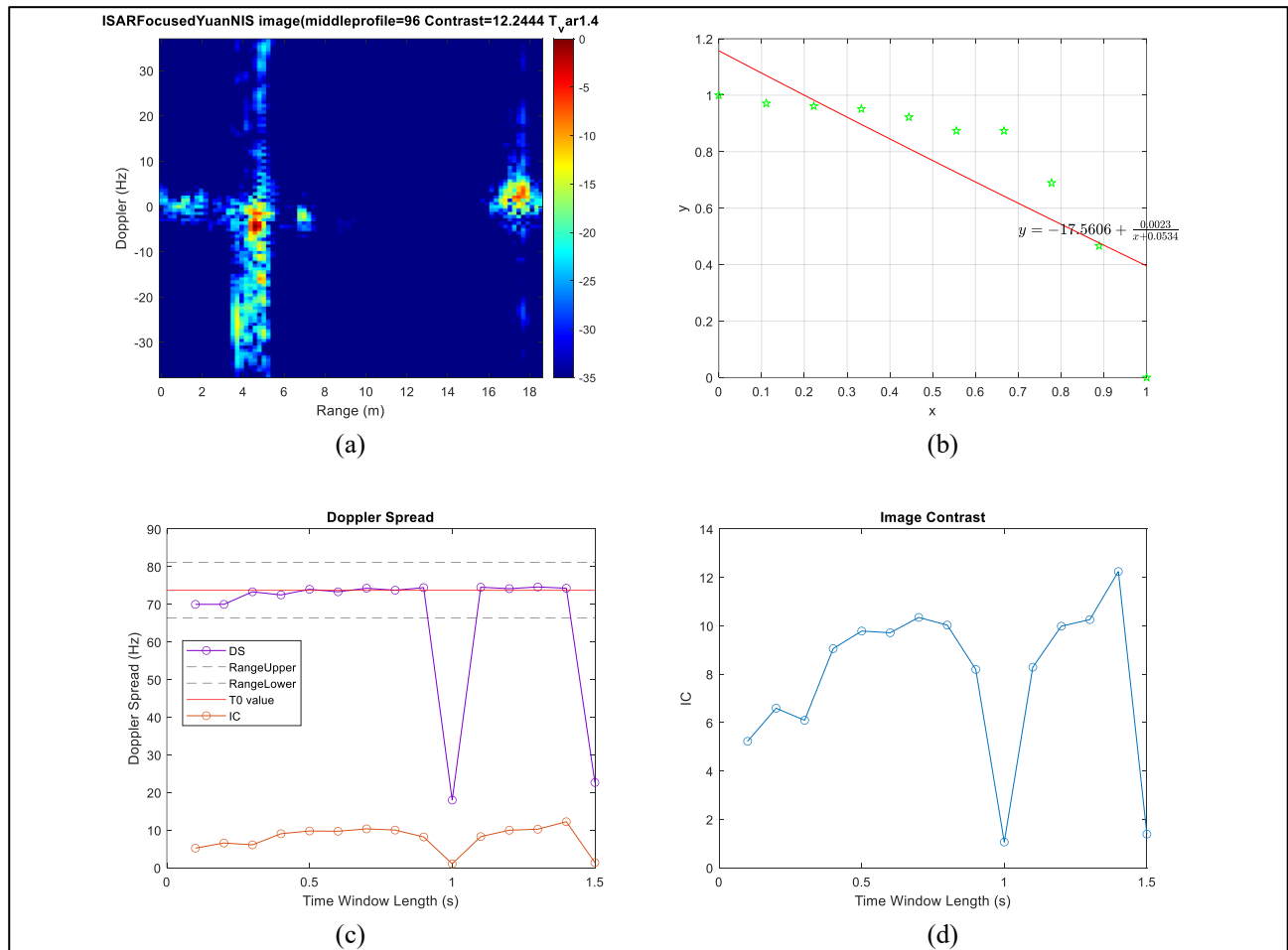


Figure 6.7 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.8(a) is the ISAR image generated for the optimum centre profile of 256, and the optimal CPTWL was found to be 1.5 seconds. The image had a contrast value of 11.2. In Fig. 6.8(b), the Doppler spread curve is shown along with its fitted hyperbola. The image contrast for the candidate CPTWL values is displayed in the plot of Fig. 6.8(d). This is then projected onto the Doppler spread plot in Fig. 6.8(c), which illustrates the

defined Doppler spread range. From Fig. 6.8(c), this candidate CPTWL of 1.5 seconds, which possessed the maximum contrast of 11.2055, had a Doppler spread that satisfied the Doppler spread range criteria. The overall ISAR image resembles the optical side-view image of the vessel with the single mast present.

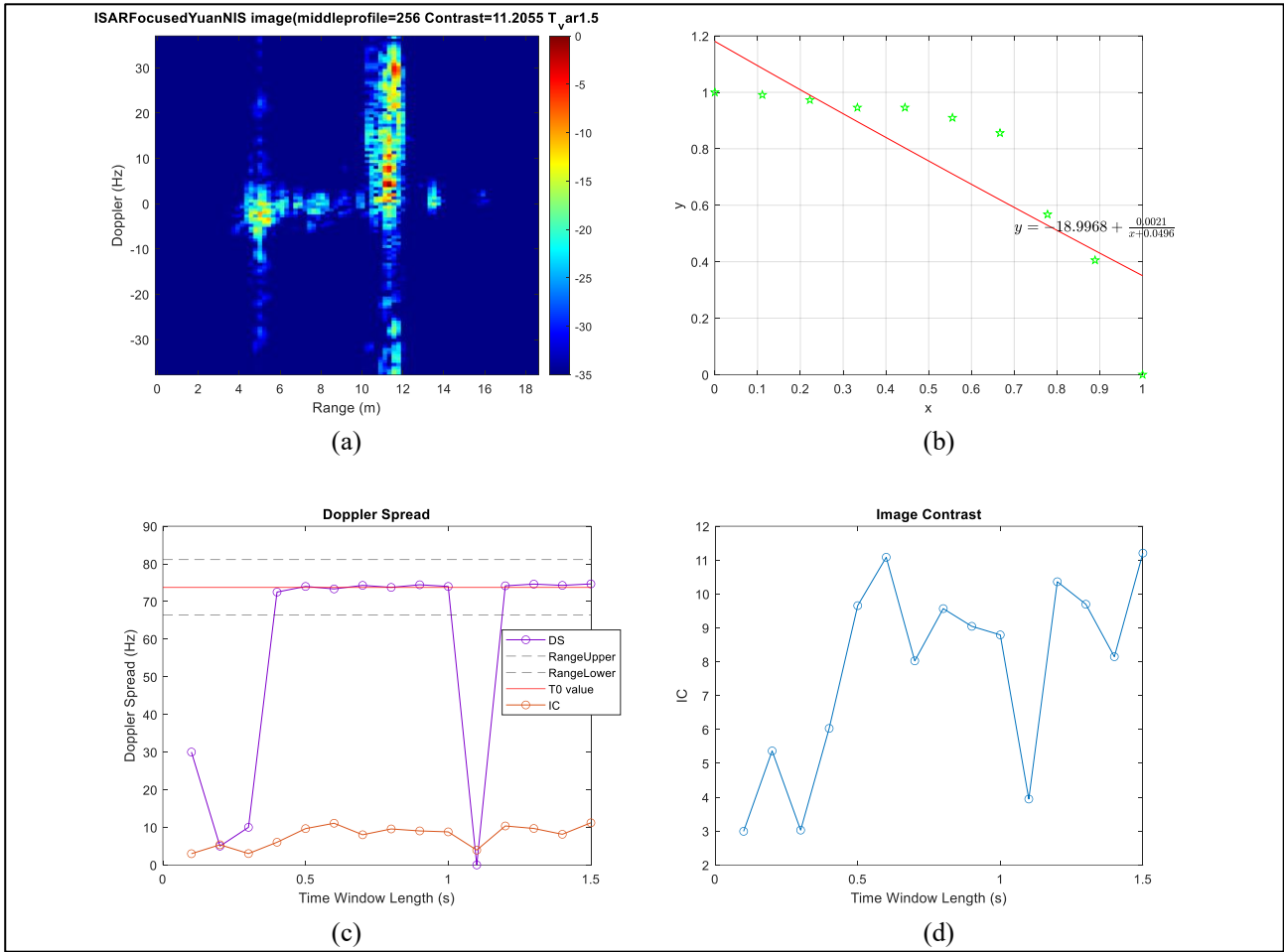


Figure 6.8 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.9(a) is the ISAR image generated for the optimum centre profile of 544. The optimal CPTWL is 0.2 seconds, and the image had a contrast value of 12.24. In Fig. 6.9(b), the Doppler spread curve is depicted as before, and the image contrast for the candidate CPTWL values is shown in the plot of Fig. 6.9(d). This is projected onto the Doppler Spread plot in Fig. 6.9(c), which depicts the specified Doppler spread range. From this plot, it can be seen that this candidate CPTWL of 0.2 seconds, which possessed the maximum contrast of 8.0459, had a Doppler spread that satisfied the Doppler spread range criteria. The overall ISAR image does not accurately resemble the optical side-view image, indicating this part of the dataset is sub-optimal.

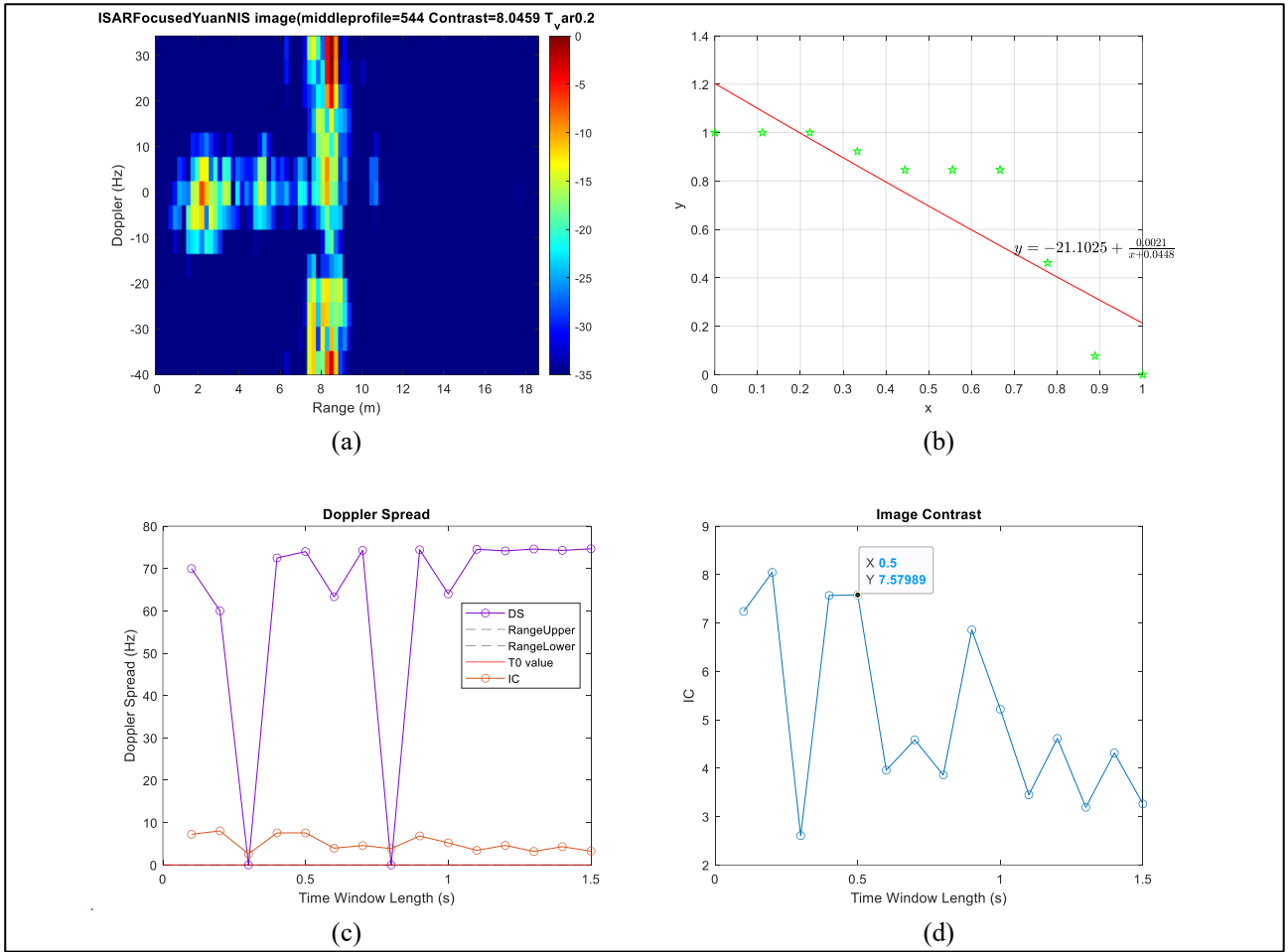


Figure 6.9 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.10(a) is the ISAR image generated for the optimum centre profile of 1120. The optimal CPTWL is 0.8 seconds in this scenario. The image had a contrast value of 18.6219. The Doppler spread curve is depicted in Fig. 6.10(b), and the image contrast for the candidate CPTWL values is shown in the plot of Fig. 6.10(d), which is then projected onto the Doppler Spread plot in Fig. 6.10(c). The candidate CPTWL of 0.8 seconds, which possessed the maximum contrast of 18.6219, satisfies the Doppler spread range criteria. The ISAR image produced resembles the optical side-view image of the vessel and would be useful for classification.

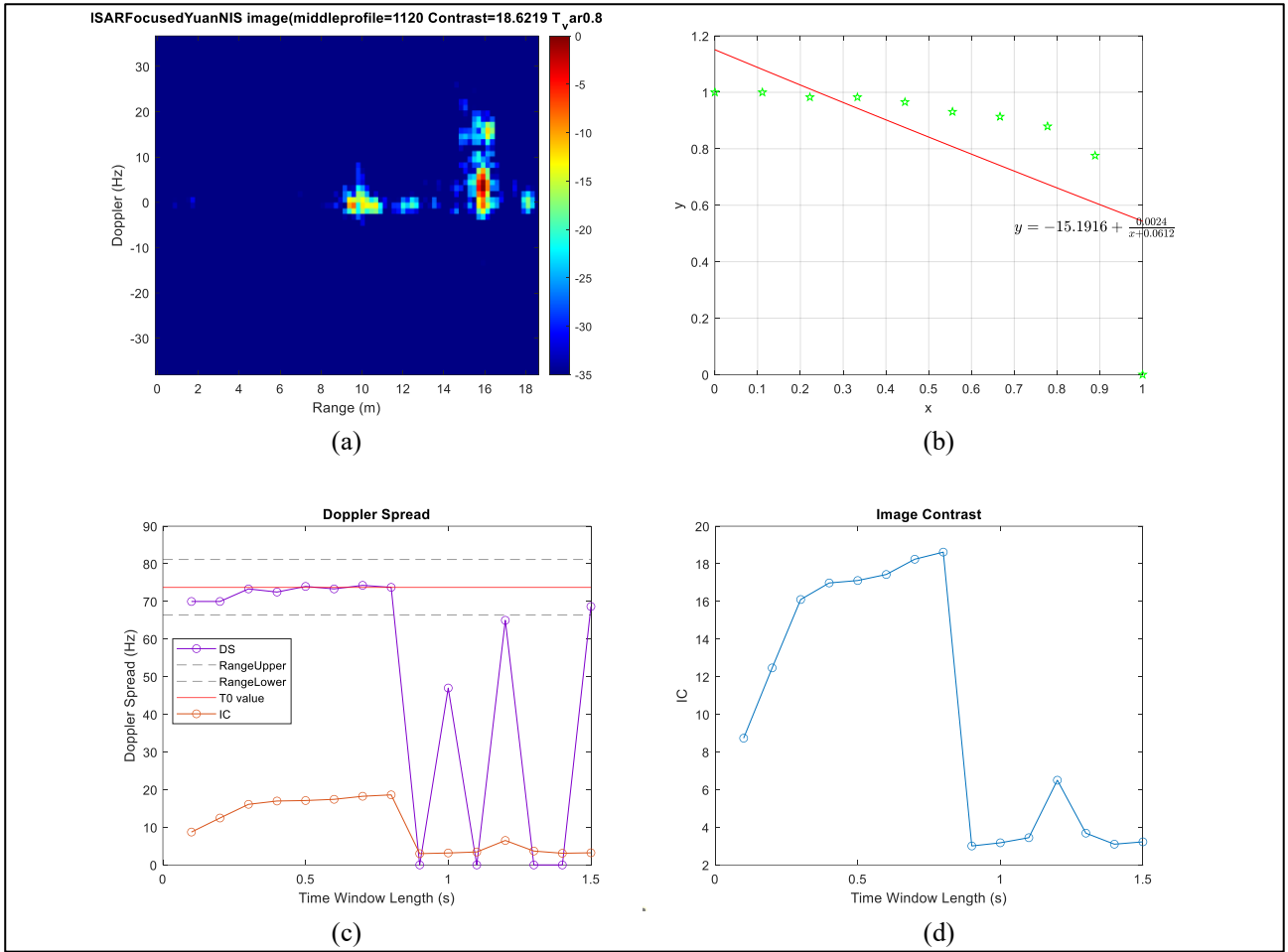


Figure 6.10 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.11(a) is the ISAR image generated for the optimum centre profile of 1280. The optimal CPTWL is 0.8 seconds in this case, with a contrast value of 17.2659. Fig. 6.11(b) presents the Doppler spread curve. The image contrast for the candidate CPTWL values is shown in the plot of Fig. 6.11(d), which is then projected onto the Doppler Spread plot in Fig. 6.11(c). The overall ISAR image does not look like the optical side-view image of the vessel. This can be improved by using a circular shift on the HRR profiles and by flipping the plot.

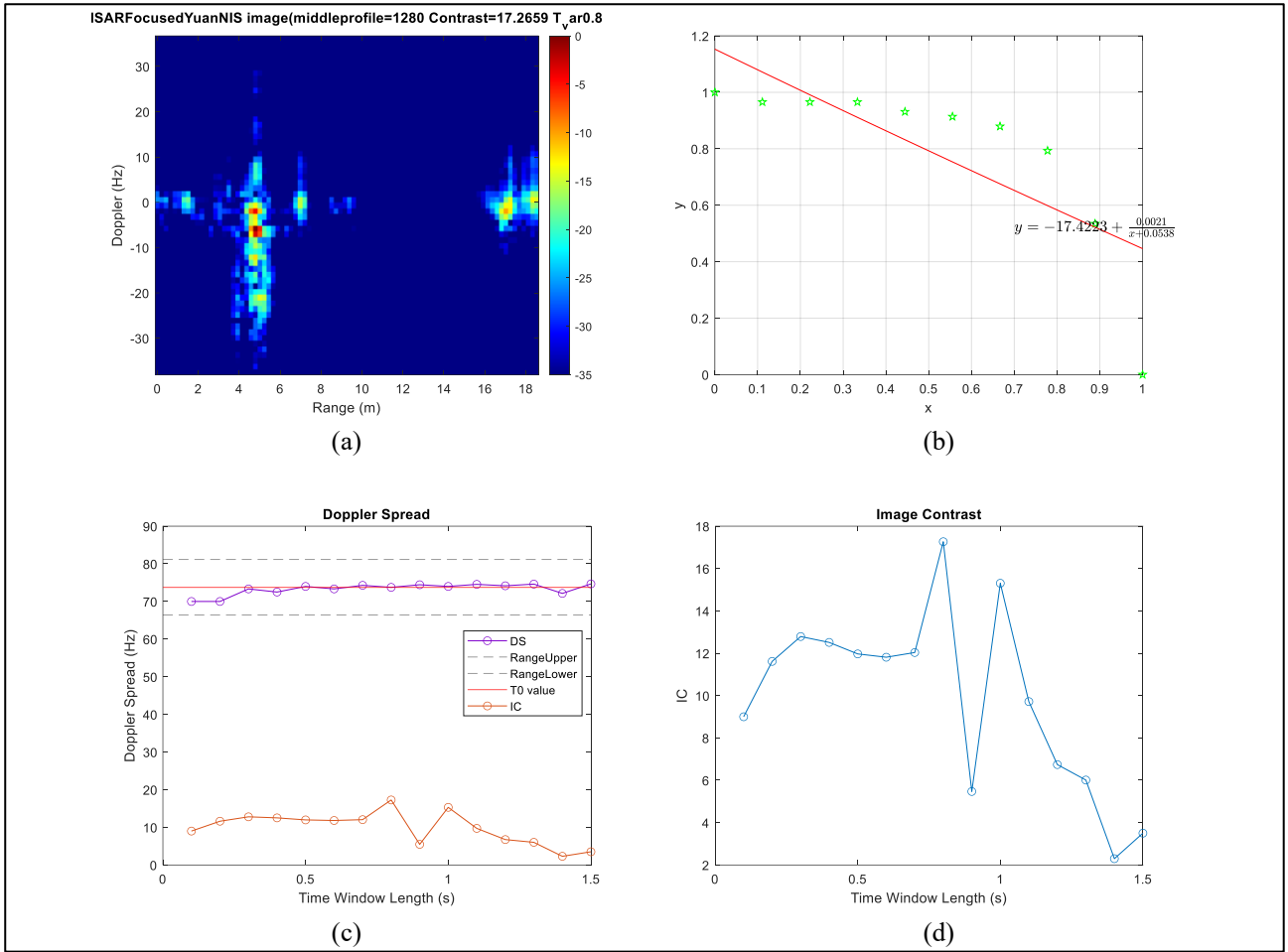


Figure 6.11 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.12(a) is the ISAR image generated for the optimum centre profile of 1440 with a contrast of 9.268 and an optimal CPTWL of 1.2 seconds. In Fig. 6.12(b), the Doppler spread curve is given. The image contrast for the selected CPTWL values is presented in the plot of Fig. 6.12(d). This is then projected onto the Doppler spread plot in Fig. 6.12(c), which illustrates the defined Doppler spread range. This candidate's CPTWL of 1.2 seconds satisfies the Doppler spread range criteria. The ISAR image does somewhat resemble the optical side-view image, with a small overlap of profiles occurring across the Doppler axis.

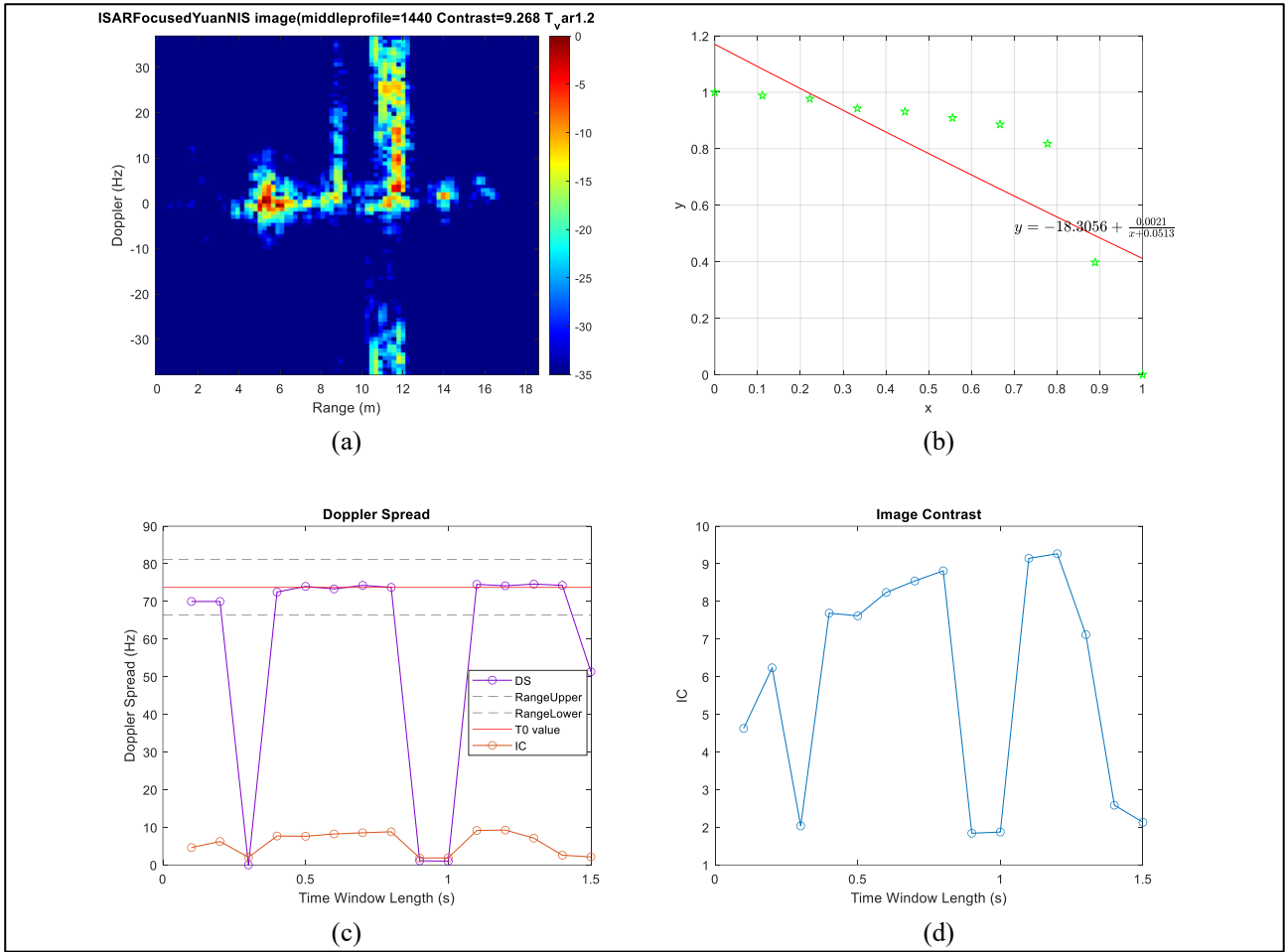


Figure 6.12 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.13(a) is the ISAR image generated for the optimum centre profile of 1536 with an optimal CPTWL of 0.3 seconds and an image contrast value of 10.7242. The Doppler spread curve is depicted in Fig. 6.13(b) with its corresponding fitted hyperbola. The image contrast for the candidate CPTWL values is shown in the plot of Fig. 6.13(d). The Doppler Spread plot is depicted in Fig. 6.13(c). The final ISAR image does not resemble the optical side-view image of the vessel without further processing, therefore, it is not suitable for classification.

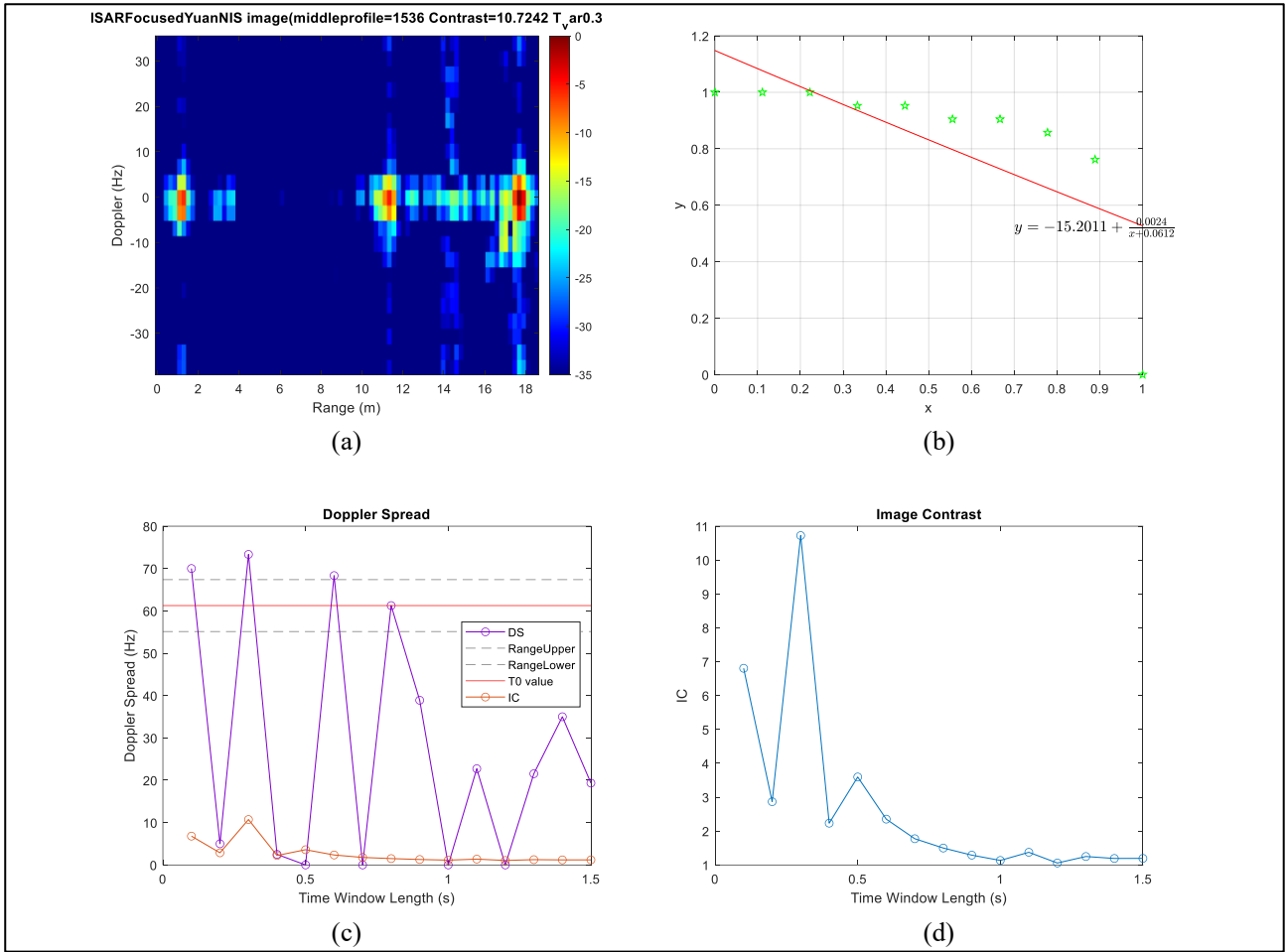


Figure 6.13 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.14(a) is the ISAR image generated for the optimum centre profile 1664. The optimal CPTWL is 1 second in this case. The image had a contrast value of 25.1046. In Fig. 6.14(b), you can see the Doppler spread curve along with the fitted hyperbola. The image contrast for the candidate CPTWL values is displayed in the plot shown in Fig. 6.14(d). This is projected onto the Doppler Spread plot in Fig. 6.14(c), which depicts that the value satisfies the range criteria. Although this ISAR image possessed the highest image contrast, there are no similarities with the optical side-view image of the vessel.

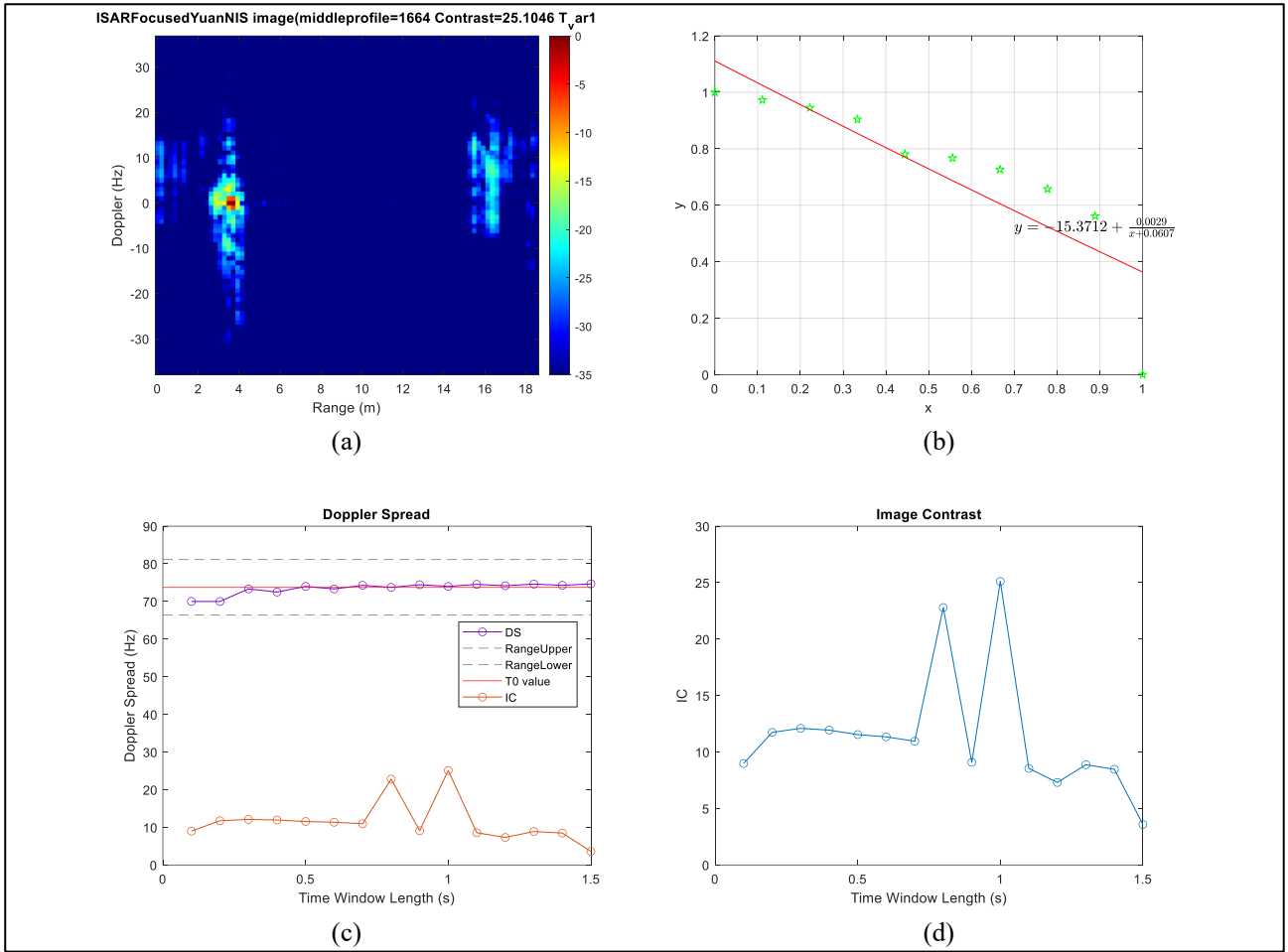


Figure 6.14 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

In total, 3 good ISAR images were found in the data recording using this method, as was seen above. They are Fig. 6.8, Fig. 6.10 and Fig. 6.12 and are justified with the qualitative and quantitative measures. An initial guess for the CPI which is closer to the ideal CPI better refines the algorithm and allows the CPI to converge more accurately. Furthermore, certain segments within the datasets do not present favourable images due to the data being inherently not ideal.

6.2.2 Zayaan Vessel

For the Zayaan vessel, the same procedure as with Umoya was followed. As before, the optimum centre profiles are first obtained. This starts by developing the spectrogram shown in Fig. 6.15, using the equations from Chapter 2.9. The initial CPTWL value was set to 0.8 seconds due to the repetition frequency of 175 Hz and the CPI of 64 profiles. Moreover, a 50% overlap was used. With the spectrogram now present, the Doppler Spread trend could be calculated by using a $k_{spec} = 1$ and this is depicted in Fig. 6.16. The local maxima in the Doppler Spread curve are the optimum centre profiles. The optimum centre profiles found, using a minimum peak prominence value of 15, are summarised in Table 6.3.

Table 6.3 Optimal centre profiles obtained

Optimum Centre Profile										
480	832	1024	2144	2560	2752	3040	3264	3584	3968	4160

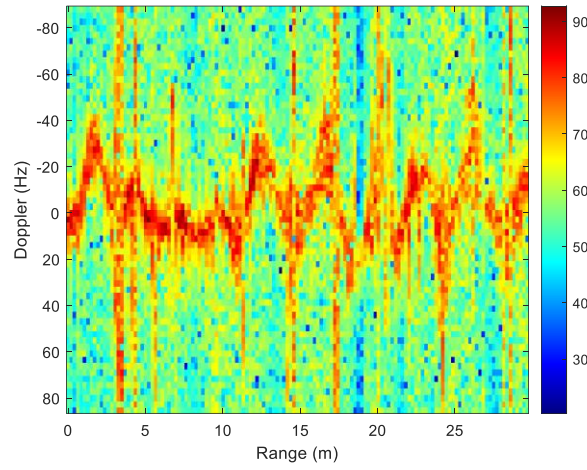


Figure 6.15 Spectrogram produced

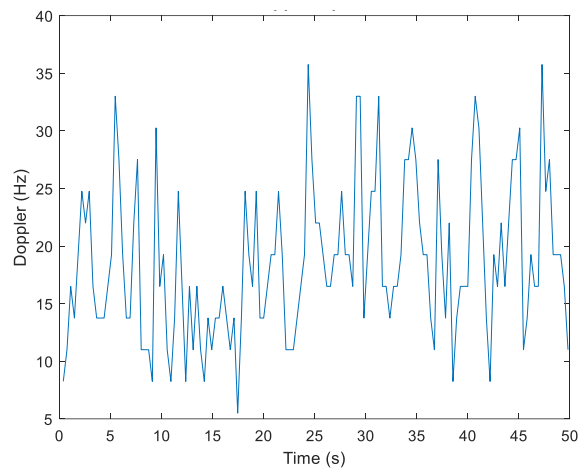


Figure 6.16 Doppler spread plot

As seen with the Umoya vessel, an optimum CPTWL was now found. Again, a set of candidate CPTWL was defined as $T=[0.1 \ 0.2 \ \dots \ 0.8 \ \dots \ 1.4 \ 1.5]$. An ISAR image for each value in T was generated before the Doppler spread was calculated. This required calculating an accurate Doppler spread of the ISAR images. Once more, to calculate the Doppler spread, the optimum threshold needed to be determined. The set of threshold candidates was defined where N_λ was again set to 10. The Doppler spread curve was then fitted with a hyperbolic curve. After normalisation, the optimum threshold was obtained, and the Doppler spread was calculated. The optimum CPTWL was then found in the same way as in Chapter 6.2.1. The range had a $k_{DS} = 0.1$. The optimum CPTWL for each optimum centre profile is given in Table 6.4.

Table 6.4 Optimal CPTWL values for each optimal centre profile

Optimal values											
Centre Profile	480	832	1024	2144	2560	2752	3040	3264	3584	3968	4160
CPTWL	0.3	1.2	0.6	0.2	0.1	0.3	1.5	1	1.4	0.2	0.8

Some of the final ISAR images, along with the plots generated in the process of forming them, are displayed in Fig. 6.17 – Fig. 6.20. The other images were left out to avoid redundancy in discussions.

Fig. 6.17(a) is the ISAR image generated for the optimum centre profile of 3584. The optimal CPTWL was 1.4 seconds. The image had a contrast value of 18.1123. In Fig. 6.17(b), the Doppler spread curve is depicted, with its corresponding fitted hyperbola. The image contrast for the candidate CPTWL values is shown in the

plot of Fig. 6.17(d). This is projected onto the Doppler Spread plot in Fig. 6.17(c), which depicts the specified Doppler spread range. From this plot, it can be observed that the candidate of 1.4 seconds, which possessed the maximum contrast of 18.1123, had a Doppler spread that satisfied the Doppler spread range criteria. The overall ISAR image does not look visually appealing as it does not accurately resemble the side view of the vessel. However, some similarities with the overall shape of the side of the vessel can be drawn.

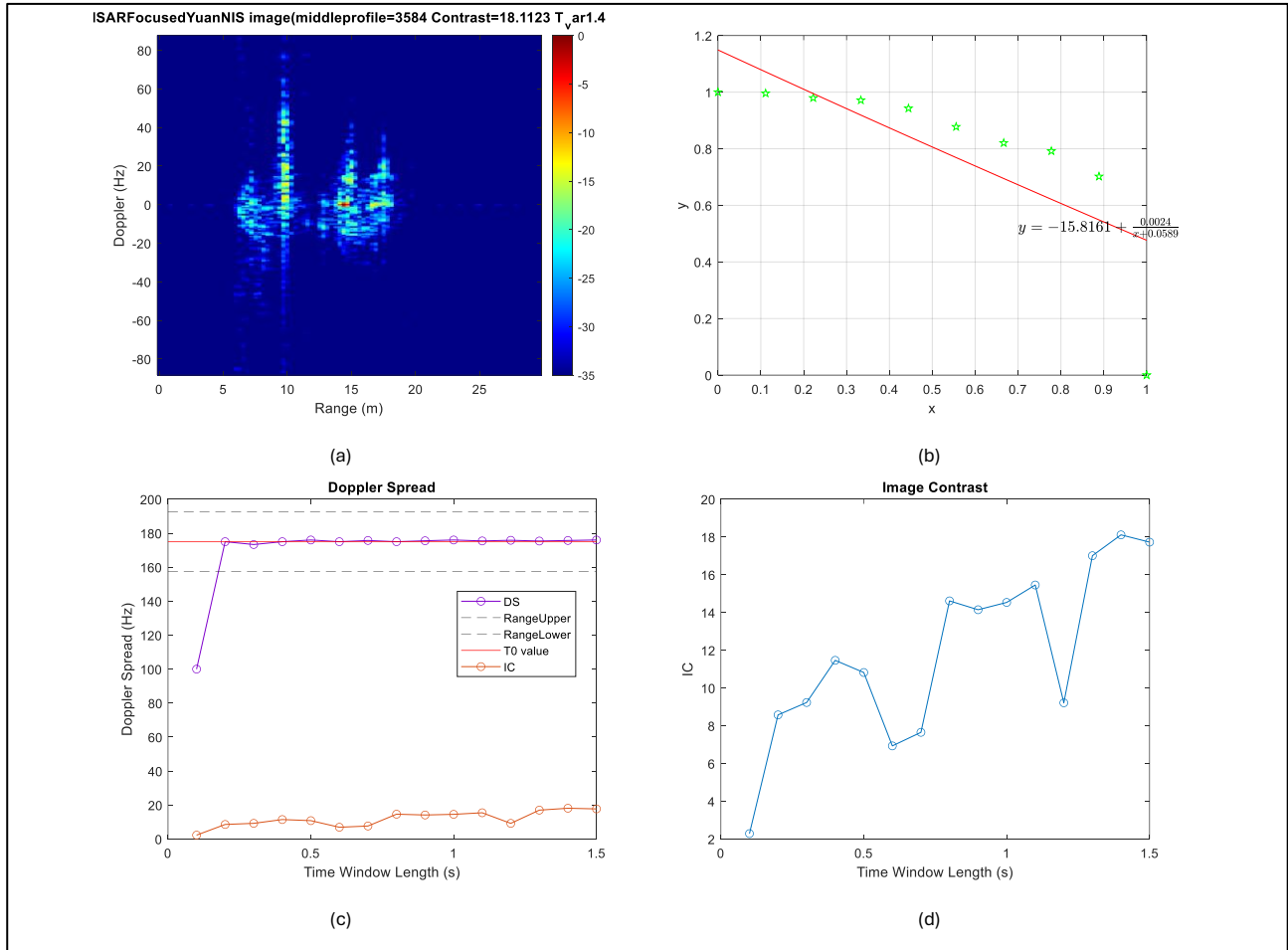


Figure 6.17 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.18(a) is the ISAR image generated for the optimum centre profile of 3264. The optimal CPTWL is 1 second in this scenario. The image had a contrast value of 14.8727. The Doppler spread curve is depicted in Fig. 6.18(b), and the image contrast for the candidate CPTWL values is shown in the plot of Fig. 6.18(d), which is then projected onto the Doppler Spread plot in Fig. 6.18(c). The candidate CPTWL of 1 second, which possessed the maximum contrast of 14.8727, satisfies the Doppler spread range criteria. The ISAR image produced resembles the optical side-view image of the vessel and would be useful for classification.

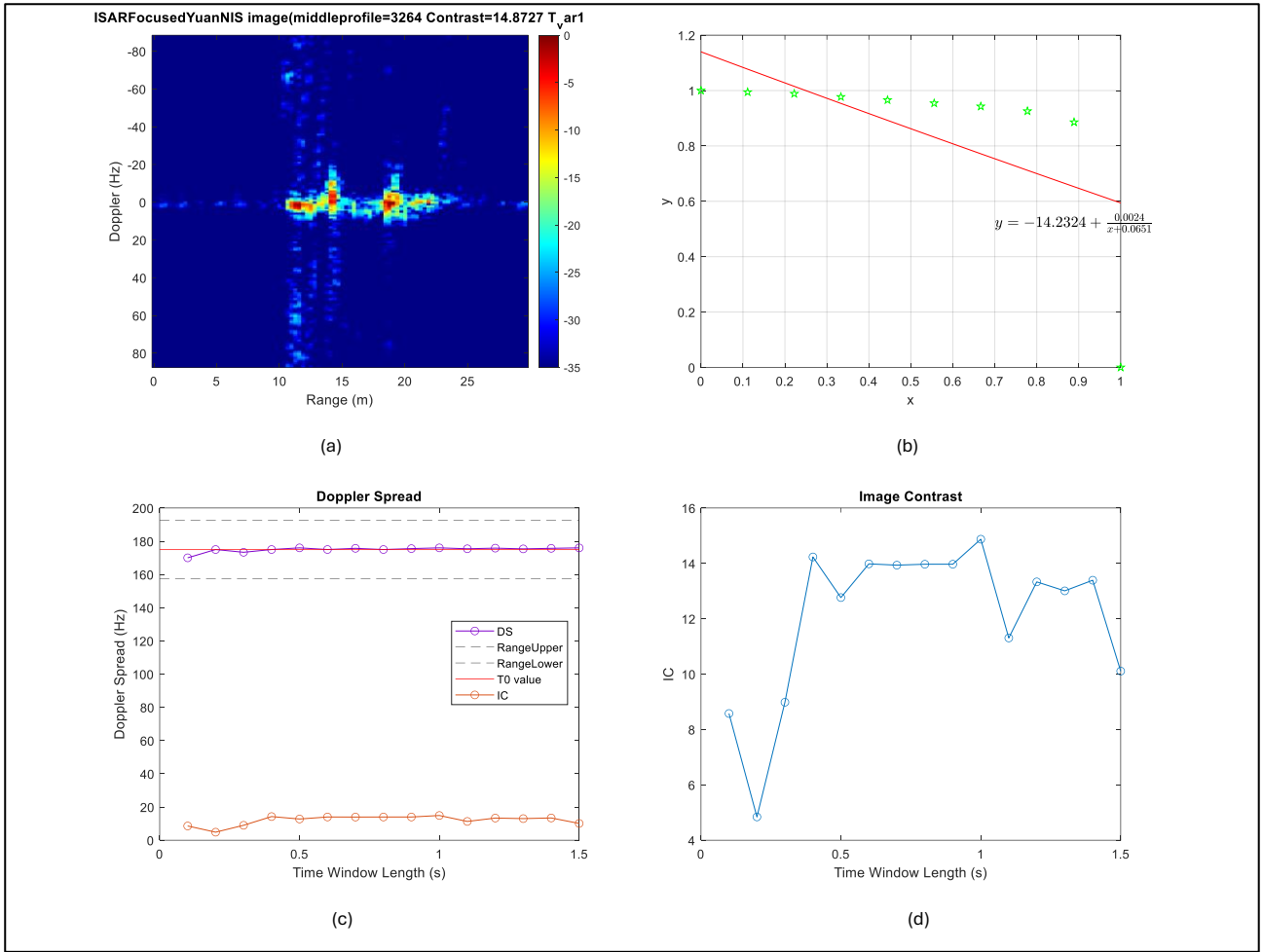


Figure 6.18 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.19(a) is the ISAR image generated for the optimum centre profile of 3040 with a contrast of 17.3689 and an optimal CPTWL of 1.5 seconds. In Fig. 6.19(b), the Doppler spread curve is given. The image contrast for the selected CPTWL values is presented in the plot of Fig. 6.19(d). This is then projected onto the Doppler spread plot in Fig. 6.19(c), which illustrates the defined Doppler spread range. This candidate's CPTWL of 1.5 seconds satisfies the Doppler spread range criteria. The ISAR image does somewhat resemble the optical side-view image, however, this is not good enough to classify the vessel. The image needs to be more focused.

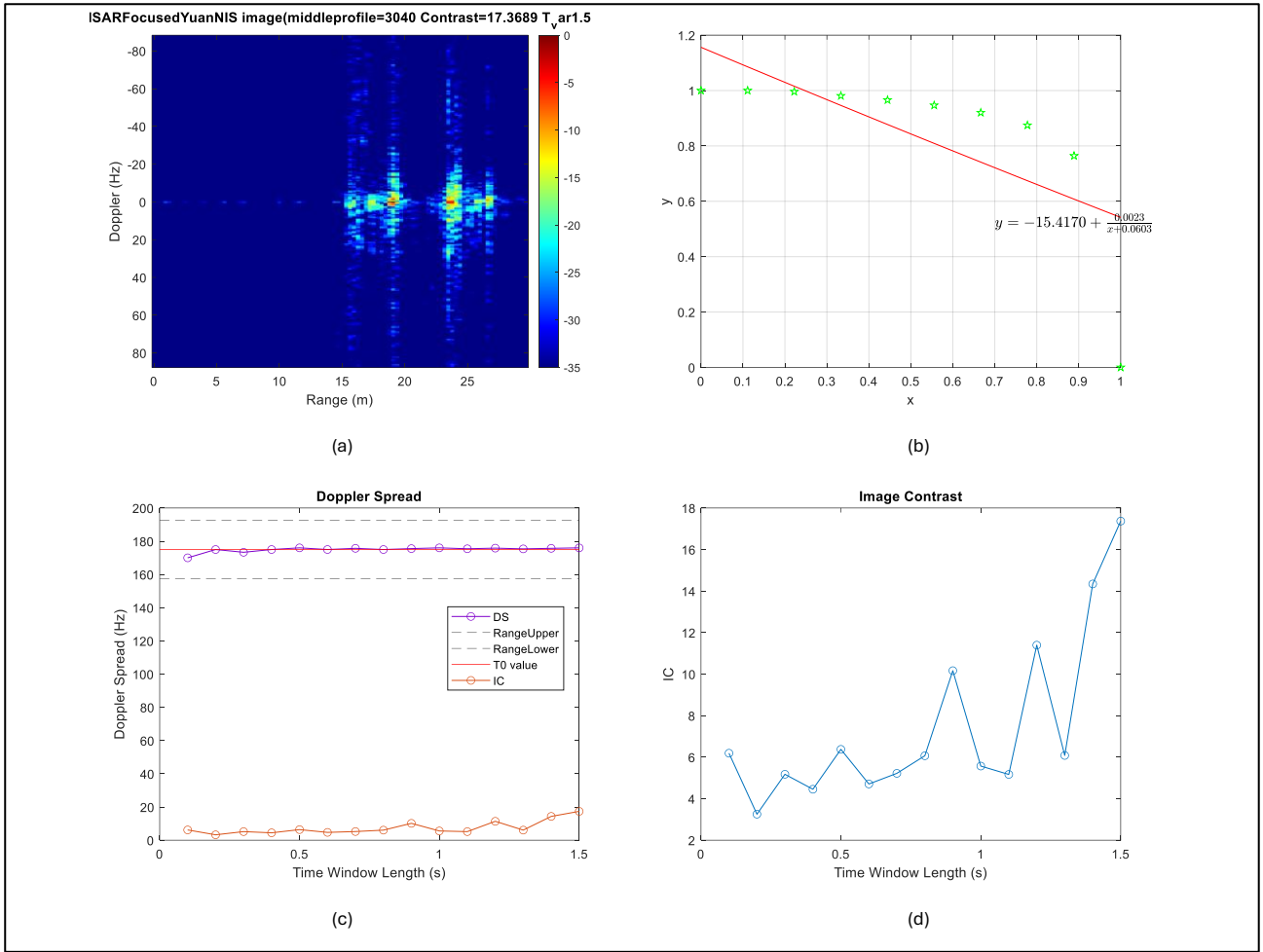


Figure 6.19 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

Fig. 6.20(a) is the ISAR image generated for the optimum centre profile of 1024. The optimal CPTWL is 0.6 seconds in this scenario. The image had a contrast value of 19.5963. The Doppler spread curve is depicted in Fig. 6.20(b), and the image contrast for the candidate CPTWL values is shown in the plot of Fig. 6.20(d), which is then projected onto the Doppler Spread plot in Fig. 6.20(c). The candidate CPTWL of 0.6 seconds, which possessed the maximum contrast of 19.5963, satisfies the Doppler spread range criteria. The ISAR image produced resembles the optical side-view image of the vessel and would be useful for classification. The image is not as focused as the one in Fig. 6.18(a), although it has a higher contrast.

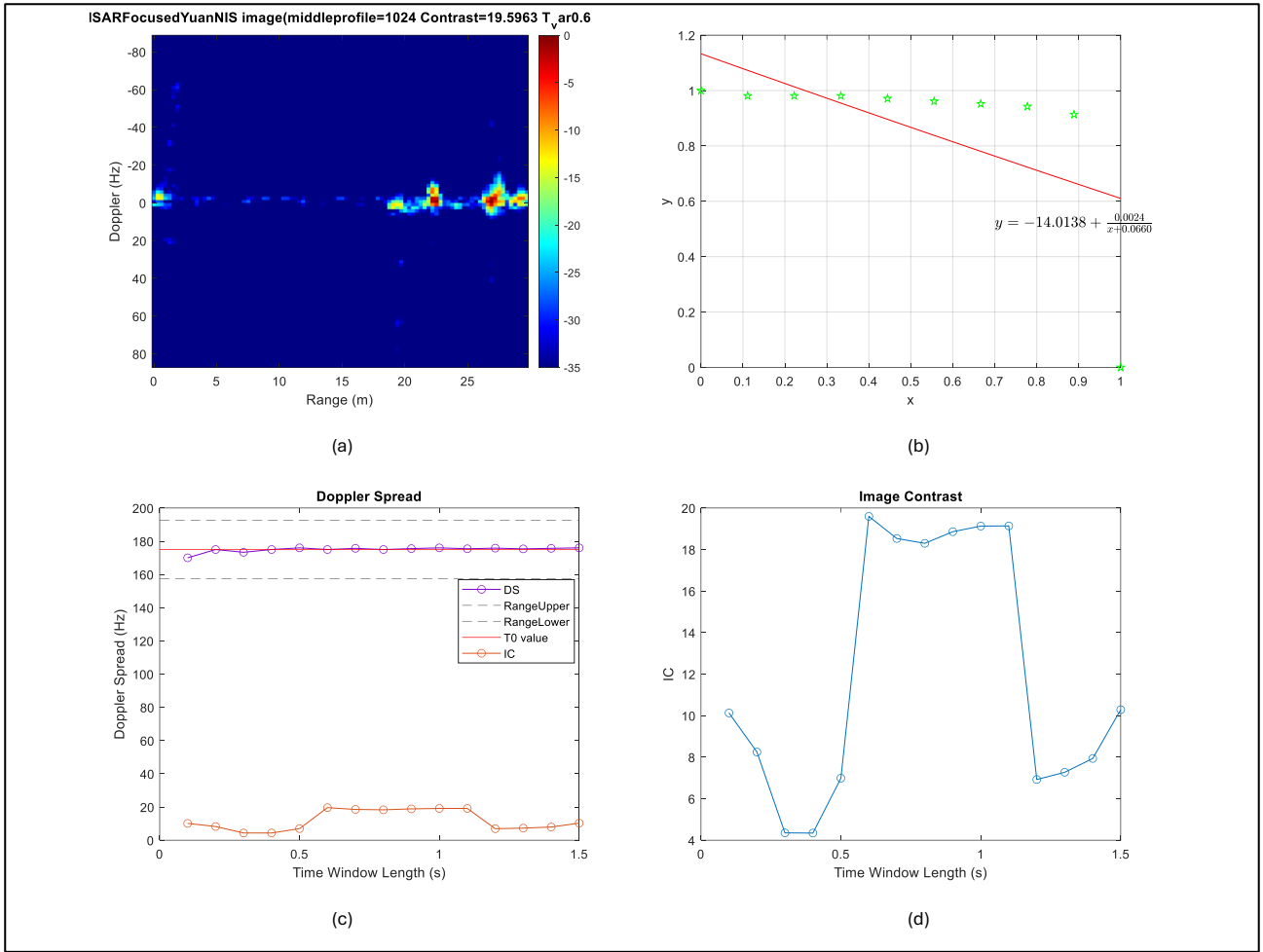


Figure 6.20 (a) ISAR image (b) Normalised Doppler Spread curve (c) Doppler Spread plot (d) Image contrast

In total 2 good ISAR images were found in the data recording using this method as was seen above. They are Fig. 6.18 and Fig. 6.20.

6.2.3 Comparison of the time window algorithms and selection for the processor

For the Umoya vessel, Fig. 6.10(a) was the ISAR image with the highest contrast, whilst still accurately resembling the side view optical image of the vessel. This strengthens the argument for Optimal CPI Selection based on Image Contrast optimisation and the Doppler Spread method, to be included in the ITWSP. The Maximum contrast-based automatic time window selection method, even had less of a restriction on the minimum peak prominence value, resulting in the method producing more ISAR images, yet still failed to produce an image with better quality measures results than Fig. 6.10. Fig. 6.2(k),(i) did produce focused visual images which compete with Fig. 6.10 arguing the case for the latter time window length method, but they fall shy in their contrast values.

For the Zayaan vessel, Fig. 6.18(a) was the ISAR image which was the most visually appealing as it most accurately resembled the side view of the optical image of the Zayaan vessel. Fig. 6.10 . Fig. 6.2(b),(d),(f),(m) did produce images that were visually appealing and with higher contrast values, however, they could not compete with the qualitative measure results seen in Fig. 6.18(a). This further strengthens the argument for Optimal CPI Selection based on Image Contrast optimisation and the Doppler Spread method, to be included in the ITWSP. Again, the Maximum contrast-based automatic time window selection method had less of a restriction on the minimum peak prominence value, resulting in the method producing more ISAR images, and once more failed to produce an image with better quantitative measurements.

Therefore, the Optimal CPI Selection based on Image Contrast optimisation and the Doppler Spread method was selected to be included in the ITWSP.

6.2.4 Conclusion

To solve the ISAR imaging CPI selection challenge, this chapter presented the results of applying the technique proposed in [12] to high-resolution radar data of two vessels. The method by Cataldo and Martorella overcame the limitations of the earlier technique proposed by Martorella in [11] by incorporating both image contrast and Doppler spread measures. Essentially, it refines the IC-based approach by adding an extra condition, that is, an ISAR image is only generated when the DS value is within a certain threshold and the image contrast value is maximum for window length selection [12]. The results indicate that, when applied to real radar data, this method produces ISAR images that contain discriminant information for operator-based classification.

7. Conclusion

7.1 Conclusion of the approach and objectives

The primary objective of this dissertation was to find robust range alignment and phase correction techniques and a combination of them to produce adequate alignment and focused ISAR images. This was accomplished by quantifying the difference in their performance, utilising theories and methods used to assess them, specifically on a range of distinct datasets, both simulated and measured. Ultimately, the objective was the development of an ITWSP to identify the focused ISAR images in long radar recordings of a sea vessel. This includes the development of a simulator to generate simulated ISAR. The objectives of the dissertation were met to the extent described below using the following systematic approach.

The dissertation began by providing the theory relating to radar as well as radar signal processing. Next, the dissertation looked at previous work done in the form of a literature review. This included reviewing range alignment algorithms, autofocus algorithms, and time window optimisation techniques, with the ultimate goal of producing focused ISAR images. Quantitative measures such as image contrast and entropy were also looked at, which would indicate the performance of the aforementioned algorithms.

A selection of the algorithms reviewed was then implemented. They were first verified using a simulator which was built to test the algorithms in a simulated environment. Next, the algorithms were tested on measured data where two maritime vessels were analysed both qualitatively and quantitatively. The qualitative measures discussed in the literature review were the same ones implemented to assist with the review of the ISAR image formation algorithms. The strengths and weaknesses of the various algorithms were discussed. The performance of the algorithms was evaluated to identify focused ISAR images from the data recordings.

A combination of robust algorithms was systematically chosen for the creation of an ITWSP. This included choosing the best range alignment algorithm, autofocus algorithm, and time window length optimisation technique. In Fig. 7.1, the ITWSP is presented where the green blocks indicate the algorithm that was selected for the particular sub-section of the processor and the red blocks indicate the algorithm that was discarded.

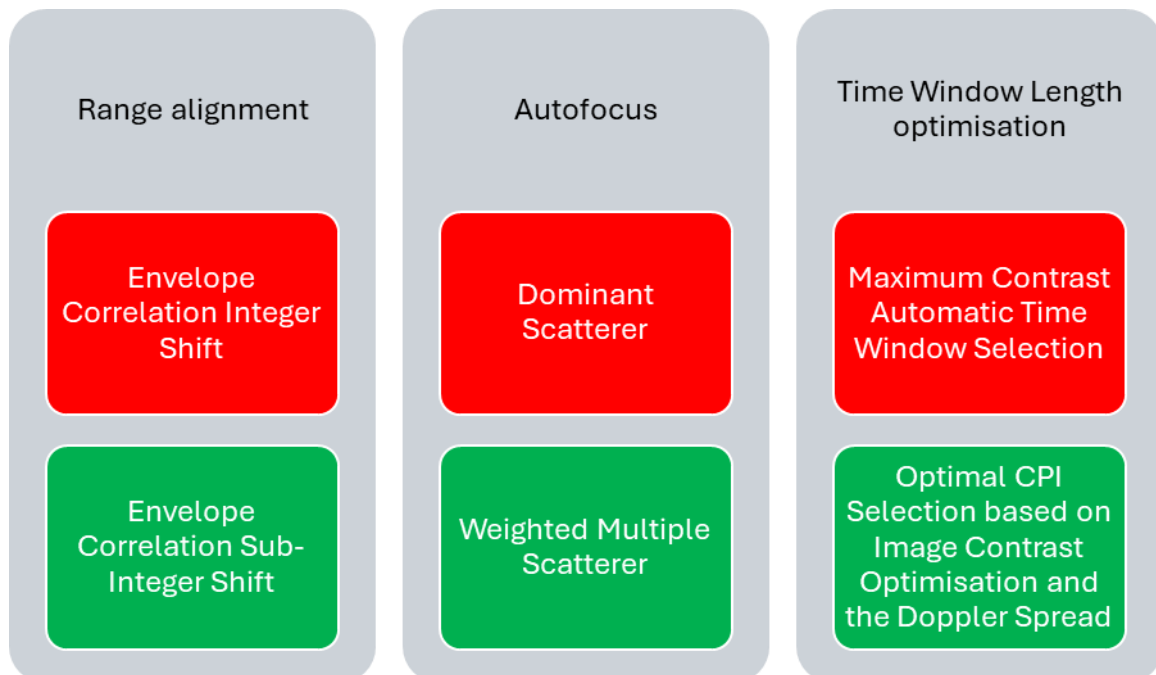


Figure 7.1 ITWSP indicated by the green blocks

The contrast values and qualitative measures were significantly better for the sub-integer shift range alignment algorithm as opposed to the integer shift alignment algorithm. Therefore, the former was an obvious choice for the processor. For the Umoya vessel, the best ISAR image had a contrast value of 19.5903 dB, when generated using the weighted multiple scatterer autofocus method. This was a slightly higher value than 19.5643dB, which was achieved using the dominant scatterer autofocus method. The contrary was seen for the Zayaan vessel, where the dominant scatterer autofocus method produced an ISAR image which had a contrast value that was 0.0171dB more than the one produced by the weighted multiple scatterer method. This indicated that the choice of the autofocus algorithm was dataset-dependent. However, the weighted multiple scatterer autofocus algorithm was selected for the ITWSP as it is more consistent across more middle profiles when chosen at random, and it produced the image with the highest contrast value across both datasets. Five good ISAR images were produced by the chosen ITWSP, which consisted of the envelope correlation sub-integer shift range alignment algorithm, the weighted multiple scatterer autofocus algorithm, and the optimal CPI selection based on image contrast optimisation and the Doppler spread technique. The single best image came from these five images for both datasets. Five good images were also seen when the maximum contrast automatic time window selection technique was used, but it did not produce the single best image for either vessel.

7.2 Future work

More work can be done to further the field of ISAR imaging, as there are many topics left out of this dissertation. The improvements discussed here are worth pursuing as enhancements in the topic of ISAR imaging could be beneficial in various fields.

7.2.1 *Implementing more range alignment and autofocus techniques*

A few range alignment and autofocus techniques, which were discussed in the literature, were not implemented. Implementing these algorithms in future iterations of the dissertation will lead to new results.

7.2.2 *Finding and implementing different quality measures*

Using more quality measures can further quantify the performance of algorithms as well as provide more measurements to distinguish the effectiveness of different algorithms. This will help with the analysis, and therefore, better conclusions could be drawn.

7.2.3 *Using larger datasets with more variety*

The dissertation only covered two types of vessels. There is a wide range of vessels that could still be explored, which would test the robustness of algorithms further.

7.2.4 *Miscellaneous*

In the future, several methods could be explored to improve ISAR imaging. One approach involves using wavelet transforms instead of the standard FFT to capture more detailed signal features. The final FFT step could be replaced with techniques such as MUSIC or ESPRIT to enhance accuracy. ISAR could also be combined with compressive sensing. Additionally, integrating ISAR with machine learning offers the potential for automatic target classification.

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Appendices

Appendix A: Steps and derivation of the Sub-Integer algorithm

Sub-integer algorithm

The following seven steps make up the sub-integer algorithm [4], [7]:

1. The first profile is given by $\overline{P}_0 = P_0$
2. The reference profile, R_m , is calculated.
3. Determine, x_m , the envelope correlation for each integer shift value of τ_m .
4. Find, $\tau_{m,0}$, which is the τ_m value which resulted in the highest cross-correlation.
5. Get the optimal shift, $\widehat{\tau}_m$, with $\tau_{m,0}$, as the initial guess to the Nelder-Mead algorithm.
6. Get the aligned profile, $\hat{P}_m$.
7. Go to step 2. ($m = m + 1$), if $m < M - 1$, where M is the number of profiles.

Haywood's algorithm

The three steps of Haywood's algorithm are as follows [4]:

1. Firstly, radial motion compensation
2. Secondly, adaptive beamforming
3. And lastly, Doppler processing

The first is explored. Assume that each of the N complex HRR profiles has n range bins as $r_1 \dots r_n$. Equation A.1 gives an HRR profile matrix of $N \times n$. [4]

$$\begin{bmatrix} r_1 \\ \vdots \\ r_N \end{bmatrix} = \begin{bmatrix} A_{11}e^{j\phi_{11}} & \dots & A_{1n}e^{j\phi_{1n}} \\ \vdots & A_{lm}e^{j\phi_{lm}} & \vdots \\ A_{N1}e^{j\phi_{N1}} & \dots & A_{Nn}e^{j\phi_{Nn}} \end{bmatrix} \quad (\text{A.1})$$

Where A_{lm} is a real number, ϕ_{lm} is a real number between $[0, 2\pi)$, $l=1 \dots N$ is an HRR profile index and m is the range bin index.

To accomplish radial correction, each HRR profile (magnitude) is cross-correlated with a reference profile provided by Equation A.2. This calculation, c_l , is shown in Equation A.3.[4]

$$r_p = [A_{p1}e^{j\phi_{p1}} \dots A_{pn}e^{j\phi_{pn}}] \quad (\text{A.2})$$

The Discrete Fourier Transform operations, DFT and IDFT, are used in Equation A.3. Equation A.4 shows that the range shift d_l , which is necessary for alignment, is indicated by the location of the peak of c_l . [4]

$$c_l = |IDFT(DFT(|r_p|)DFT(|r_l|)^*)| \quad \forall l = 1 \dots N \quad (\text{A.3})$$

$$d_l = \text{location}[\max(c_l)] \quad \forall l = 1 \dots N \quad (\text{A.4})$$

To smooth the shift sequence, $d_1 \dots d_n$, a low-order polynomial is fitted to it. In the frequency domain, the HRR profiles are multiplied by a phase shift vector, Φ , to apply the smoothed sub-integer shifts, s_l . The calculation is shown in Equation A.5 with Φ shown in Equation A.6. [4]

$$r'_l = IDFT(\Phi DFT([A_{l1}e^{j\phi_{l1}} \dots A_{lm}e^{j\phi_{lm}} \dots A_{ln}e^{j\phi_{ln}}])) \quad \forall l = 1 \dots N \quad (\text{A.5})$$

$$\Phi = e^{j\frac{2\pi}{\beta}} \times [e^{-js_l(f_s+\Delta f)} \dots e^{-js_l(f_s+m\Delta f)} \dots e^{-js_l(f_s+n\Delta f)}] \quad \forall l = 1 \dots N \quad (\text{A.6})$$

Where the bandwidth is represented by $\beta = N\Delta f$, f_s is the start frequency Δf and is the frequency increment. The HRR profiles are represented by Equation A.7, after range alignment.

$$\begin{bmatrix} r'_1 \\ \vdots \\ r'_N \end{bmatrix} = \begin{bmatrix} A'_{11}e^{j\phi'_{11}} & \dots & A'_{1n}e^{j\phi'_{1n}} \\ \vdots & A'_{lm}e^{j\phi'_{lm}} & \vdots \\ A'_{N1}e^{j\phi'_{N1}} & \dots & A'_{Nn}e^{j\phi'_{Nn}} \end{bmatrix} \quad (\text{A.7})$$

Where A'_{lm} is real, ϕ'_{lm} is a real number between $[0, 2\pi)$, $l=1 \dots N$ is an HRR profile index and m is the range bin index.

Appendix B: The Global Method Process

Equation B.1 is used to calculate the shift value, τ_m , applied to profile m [4], [25]:

$$\tau_m = \sum_{i=1}^{\infty} \beta(i) \left(\frac{2m}{M} - 1 \right)^i \quad (\text{B.1})$$

The algorithm presented in Fig.B.1 calculates the value, $\beta(i)$ [4].

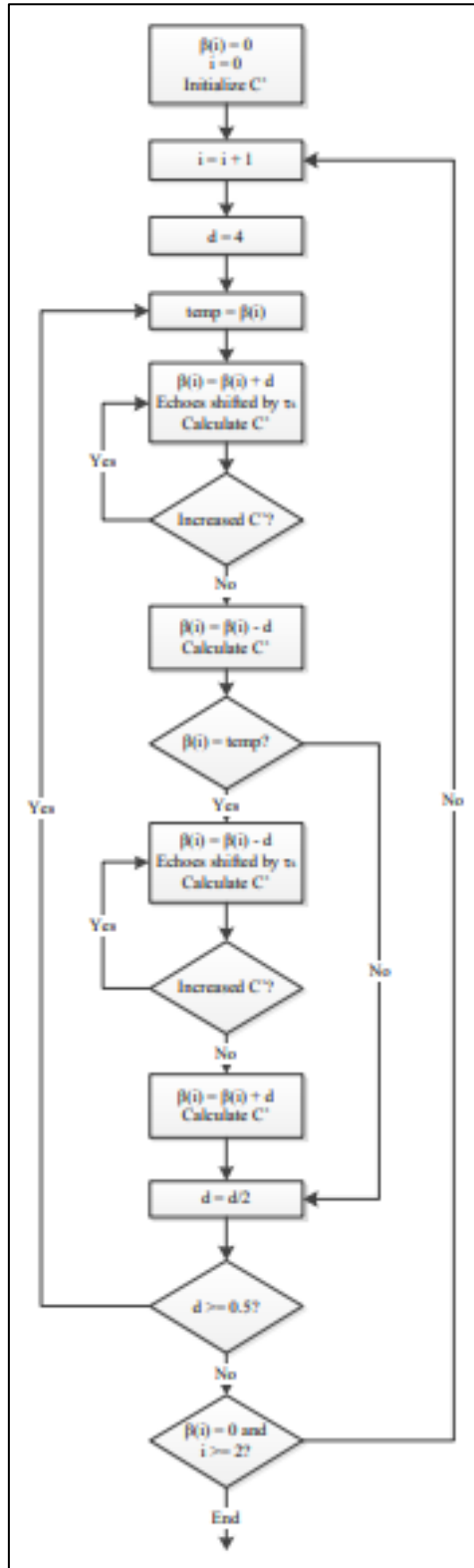


Fig. B.1: Algorithm to calculate $\beta(i)$ [4]

Appendix C: The Sum Envelope Entropy

The sum envelope defined in Equation C.1 is made use of in the sum envelope entropy which was presented in [33]. [4]

$$H = - \sum_{n=0}^{N-1} \frac{a(n)}{A} \ln \frac{a(n)}{A} \quad (\text{C.1})$$

Where n , N , and A stay the same as previously stated.

Although the envelopes of different profiles in a data set have varied time delays, they share a similar shape. As a result, when the profiles align, $a(n)$ is the sharpest, and the entropy, H , is at a minimum. Equation C.1 is rewritten as Equation C.2. [4]

$$H = \ln A - \frac{1}{A} \sum_{n=0}^{N-1} a(n) \ln a(n) \quad (C.2)$$

Equation C.3, which is calculated more efficiently than Equation C.1, redefines H since A remains constant in alignment. [4]

$$H' = - \sum_{n=0}^{N-1} a(n) \ln a(n) \quad (C.3)$$

Appendix D: Intra-data set performance of different range alignment algorithms

A comparison was done on the Zayaan vessel dataset to assess the performance of the different range alignment algorithms. Fig. D.1 presents the results of the integer shift algorithms whereas Fig. D.2 presents the results of the sub-integer shift algorithms.

When applying the integer shift algorithms to various data blocks, the contrast values that are produced can differ considerably. This can be seen in Fig. D.1, where the techniques are distinguished by a legend. For readability, the contrast values, which varied from -24 dB to -15.5 dB, were normalised (divided by unaligned value). For the majority of the dataset, it is clear that the single reference approach generated the highest contrast values. Regarding the red troughs, it should be noted that because of the negative signs of the values, a lower normalised value corresponds to a larger contrast value. It is crucial to remember that, despite the non-coherent cumulative averaging method's several dominant troughs, altering the sliding window may yield the same or a better result for the sliding window (s-w avg) method.

When applying the sub-integer shift algorithms to various data blocks, the contrast values that are produced can differ greatly. This can be seen in Fig. D.2, where the procedures are distinguished by a legend. For readability, the contrast, which varied from -27.5 dB to -15.5 dB, was normalised. It was possible to determine from the plot which algorithms performed best at which blocks in terms of contrast.

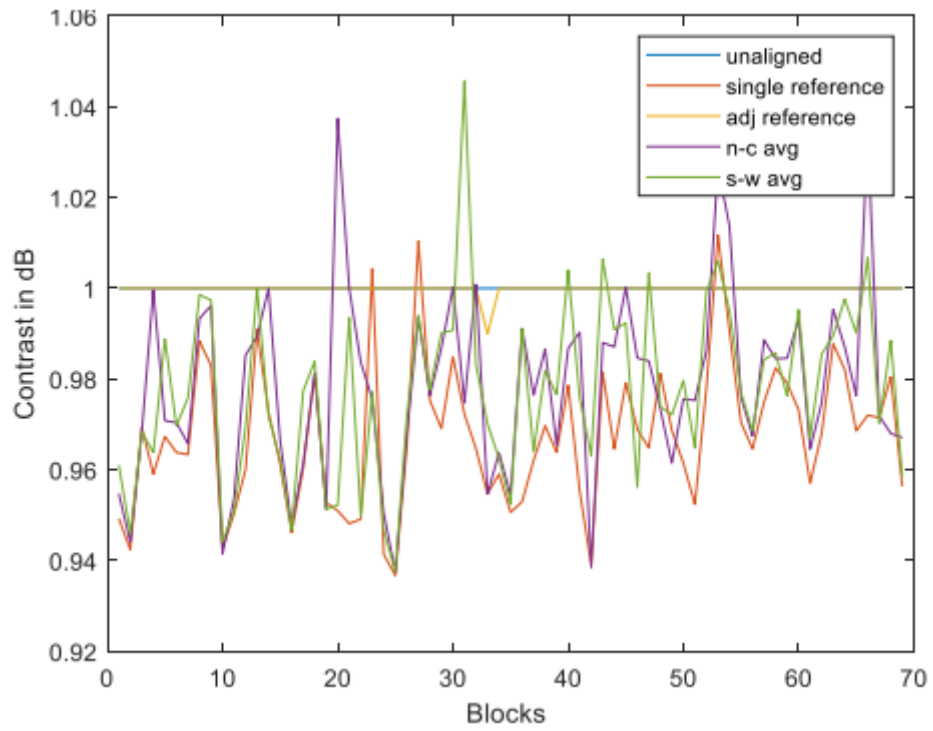


Fig. D.1: Blocks vs normalised contrast (dB)

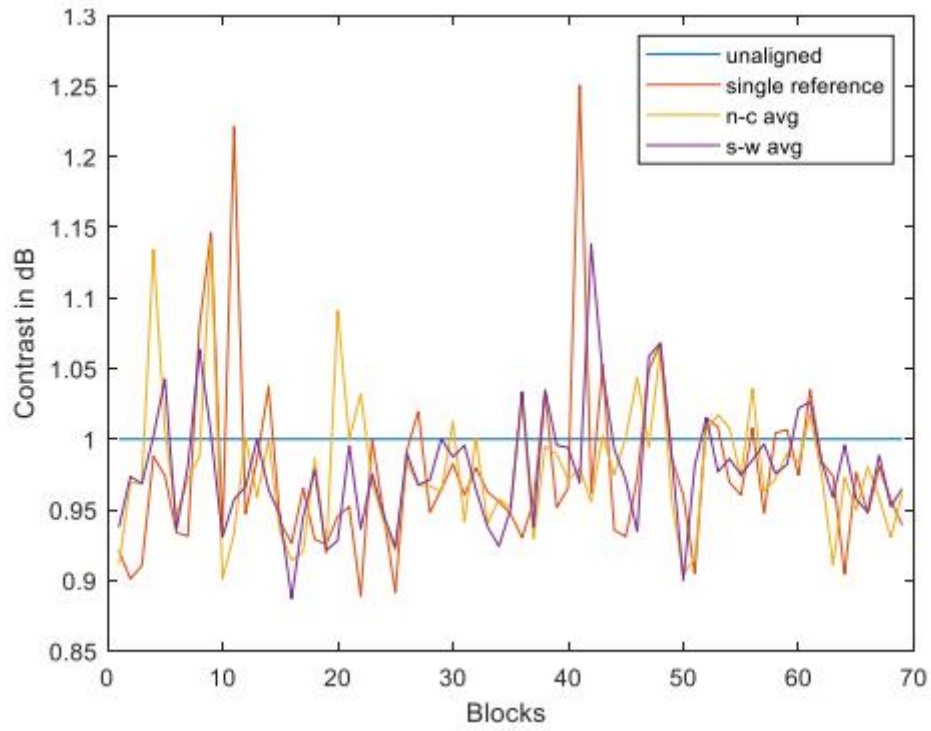


Fig. D.2: Blocks vs normalised contrast (dB)