Autonomous Weld Joint Detection and Localisation Using Computer Vision in Robotic Arc Welding

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A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

School of Computing, Engineering and Mathematics
University of Western Sydney
October 2013
Dedication

I dedicate this thesis to my Mum. The strongest person I know. She gives me the strength to follow my dreams.
Acknowledgements

I would dearly like to thank my supervisory panel, Dr. Gu Fang, Dr. Ju Jia Zou and Prof. Yang Xiang for their years of support. Without their help, this thesis would not have been possible. I would especially like to thank my principal supervisor Dr. Gu Fang. It is hard to express in words just how crucial his support has been. I am truly honoured to be under his tutelage.

I would like to thank my employer and corporate sponsor, The Lincoln Electric Company Australia and the Australian Research Council for funding my research under project ID LP0991108.

A special thank you to my family and friends for their support and encouragement over the years.

I will always be grateful to my former mentor, John Cameron for giving me the opportunity at Lincoln and letting me convince him that this was a good idea. I would like to thank my second family in the Lincoln Automation Division, “Uncle” Louie Tulissio, Mendo Popovski, Garry Vanzin Frans Kuvener, Paul Howe, Maurice Abromas, Andrew Crawford, Denise Bull and Brock Dominish. I could not have asked for a better bunch of people to work with.

I gratefully acknowledge the support of the undergraduate students Kevin Micallef, William Croft, Albert Mahoney and Nicholas Kharoufeh for their contributions. I would also like to acknowledge the support of my fellow PhD candidates at UWS for keeping it real and making this experience an enjoyable one. Thank you to the technical staff at UWS for setting up the robotic welding workshop. Finally, Zhen Ye and Yanling Xu from Shanghai Jaio Tong University for travelling to Australia away from their family and friends to contribute to this project.
Statement of Authentication

The work presented in this thesis is, to the best of my knowledge and belief, original except as acknowledged in the text. I hereby declare that I have not submitted this material, either in full or in part, for a degree at this or any other institution.

Mitchell Dinham
# Table of Contents

Table of Contents ........................................................................................................ i

List of Tables .................................................................................................................. vii

List of Figures .................................................................................................................. viii

List of Abbreviations ..................................................................................................... xvii

Abstract .......................................................................................................................... xviii

Chapter 1  Introduction .................................................................................................. 1

  1.1 Background .............................................................................................................. 1
  1.3 Aim of the Thesis .................................................................................................... 4
  1.4 Contribution of the Thesis ..................................................................................... 5
  1.5 Publications ............................................................................................................. 6
  1.6 Structure of the Thesis .......................................................................................... 8

Chapter 2  Literature Review ......................................................................................... 9

  2.1 Camera Calibration ............................................................................................... 9
    2.1.1 Introduction ...................................................................................................... 9
    2.1.2 Camera Model ................................................................................................. 10
    2.1.3 Automatic Camera Calibration ....................................................................... 14
  2.2 Robot and Hand-Eye Calibration ........................................................................... 16
    2.2.1 Introduction ...................................................................................................... 16
    2.2.2 Robot Kinematic Model .................................................................................. 16
    2.2.3 Classic Hand-Eye Calibration ......................................................................... 19
2.2.4 Robot Calibration ..............................................................................................................20
2.2.5 Optimised Hand-Eye Calibration .......................................................................................22
2.3 Weld Joint Detection .............................................................................................................24
  2.3.1 Introduction ......................................................................................................................24
  2.3.2 Global Weld Joint Detection ...........................................................................................25
  2.3.3 Local Weld Joint Detection .............................................................................................29
2.4 Weld Joint Localisation .........................................................................................................33
  2.4.1 Introduction ......................................................................................................................33
  2.4.2 Epipolar Geometry ...........................................................................................................34
  2.4.3 Planar Homography .........................................................................................................36
  2.4.4 Pixel Intensity Matching ..................................................................................................39
  2.4.5 Triangulation ...................................................................................................................41
  2.4.6 Weld Joint Localisation ...................................................................................................43
2.5 Summary ..................................................................................................................................46
  2.5.1 Research Gap in Robot and Hand-Eye Calibration .........................................................46
  2.5.2 Research Gap in Weld Joint Detection ............................................................................47
  2.5.3 Research Gap in Weld Joint Localisation ........................................................................49

Chapter 3  Methodology ................................................................................................................50

  3.1 Simultaneous Calibration of an Eye-in-Hand Stereo Vision System and Arc Welding Robot ..................................................................................................................50
    3.1.1 Introduction .....................................................................................................................50
3.1.2 Co-ordinate Convention System .................................................. 51
3.1.3 Stereo Calibration ........................................................................ 53
3.1.4 Initialisation of the Robot-World Transformation ........................... 54
3.1.5 Initialisation of the Hand-Eye Transformation ................................ 56
3.1.6 Optimised Simultaneous Calibration of the Robot, Hand-Eye and Robot-World Transformations ............................................................... 58
3.1.7 The Proposed Automated Camera Calibration Method .................... 63
  3.1.7.1 Origin Point Recognition ............................................................. 65
  3.1.7.2 Remaining Calibration Board Boundary Points ........................... 68
3.2 Planar Weld Joint Detection ................................................................ 70
  3.2.1 Introduction .................................................................................. 70
  3.2.2 Pre-processing .............................................................................. 71
    3.2.2.1 Image conversion and smoothing ............................................. 71
    3.2.2.2 Pre-processing Edge Identification ........................................... 73
  3.2.3 Background Segmentation ............................................................. 74
    3.2.3.1 Hough Lines ........................................................................... 74
    3.2.3.2 Search Windows ..................................................................... 76
  3.2.4 Weld Joint Detection .................................................................... 80
    3.2.4.1 Edge Identification in Foreground Image .................................... 80
    3.2.4.2 Work Piece Boundary Removal ............................................... 81
    3.2.4.3 Weld joint Seam Line Detection ............................................... 82
    3.2.4.4 Post-processing of the Weld joint Seam Line .............................. 83
3.3 Image Matching for Planar Weld Joints .........................................................85
3.3.1 Introduction .........................................................................................85
3.3.1 Corner Feature Detection .................................................................86
3.3.3 Homography Calculation .................................................................87
3.3.4 Image Matching and Triangulation ....................................................87
3.4 Combined Planar and Non Planar Weld Joint Detection .....................88
3.4.1 Introduction .........................................................................................88
3.4.2 Initial Seed Placement .........................................................................89
3.4.3 Initial Welding Seam Line Growing Algorithm ...............................91
3.4.4 Calculating the final Seed Location ....................................................98
3.4.5 Final Welding Seam Algorithm ..........................................................102
  3.4.5.1 Overview of final line growing stage .................................................102
  3.4.5.2 Edge Tolerance ...............................................................................103
  3.4.5.3 End Trimming ...............................................................................106
3.5 Image Matching for the Combined Planar and Non Planar Weld Joints ......114
3.5.1 Introduction .........................................................................................114
3.5.2 Reference Point Selection .................................................................114
3.5.3 Intersection Points .............................................................................115
3.5.3 Matching Criteria - Single Intersection .............................................116
3.5.4 Matching Criteria - Multiple Intersections ........................................116
3.6 Summary ...............................................................................................117
Chapter 4  Results and Discussion

4.1 Experimental Setup

4.2 Optimised Robot and Hand-Eye Calibration Results

4.2.1 Calibration Setup

4.2.2 Camera Intrinsic Parameter Calibration Results

4.2.3 Stereo Calibration

4.2.4 Initialisation of the Denavit-Hartenberg Parameters

4.2.4 Initialisation of the Robot-World Transformation

4.2.5 Initialisation of the Hand-Eye Transformation

4.2.5 Optimisation Results

4.2.6 Verification of the Calibration Accuracy

4.3 Butt Weld Joint Detection and Localisation Results

4.3.1 Work Piece Case Studies

4.3.2 Butt Weld Joint Detection Results

4.3.2.1 Case Study 1 – Saw Tooth

4.3.2.2 Case Study 2 – Curve

4.3.2.3 Case Study 3 – S shape

4.3.3 Butt Weld Joint Detection Comparison

4.3.4 Butt Weld Joint Image Matching Results

4.3.4.1 Test points

4.3.4.2 Proposed Homography Estimation Results
List of Tables

Table 1: Camera Intrinsic Parameter Results ................................................................. 123
Table 2: Nominal DH parameters for a Fanuc ArcMate 100iC ........................................ 125
Table 3: Touch points for initial Robot-World transformation ......................................... 125
Table 4: Geometrical variations for the robot-world transformation .................................. 128
Table 5: Geometrical variations for the hand-eye transformation ..................................... 128
Table 6: Tolerance variations for the robot kinematic model ........................................... 128
Table 7: Actual D-H parameters after optimisation ......................................................... 128
Table 8: Robot joint angles for calibration test positions ................................................. 131
Table 9: Image matching pixel error for case study 1 ..................................................... 173
Table 10: Image matching pixel error for case study 2 .................................................... 173
Table 11: Image matching pixel error for case study 3 .................................................... 174
Table 11: Localisation error case study 1 ................................................................. 175
Table 12: Localisation error case study 2 ................................................................. 176
Table 13: Localisation error case study 3 ................................................................. 178
Table 14: Matching error for case study 1 ................................................................. 207
Table 15: Matching error for case study 2 ................................................................. 208
Table 16: Matching error for case study 3 ................................................................. 209
Table 17: Matching error for case study 4 ................................................................. 210
Table 18: Matching error for case study 5 ................................................................. 212
Table 19: Matching error for case study 6 ................................................................. 213
Table 20: Localisation error for case study 1 ................................................................. 216
Table 21: Localisation error for case study 2 ................................................................. 217
Table 22: Localisation error for case study 3 ................................................................. 217
Table 23: Localisation error for case study 4 ................................................................. 217
Table 24: Localisation error for case study 5 ................................................................. 217
Table 25: Localisation error for case study 6 ................................................................. 217
List of Figures

Figure 2.1: Calibration board images taken during camera calibration [13] ..........10
Figure 2.2: Pinhole Camera Model [15] ................................................................10
Figure 2.3: Projective transformation relationships ..............................................14
Figure 2.4: Hand-eye geometrical transformation overview ...............................18
Figure 2.5: Classic AX=XB [26] ........................................................................19
Figure 2.6: Types of butt and fillet weld joint configurations[57] ......................25
Figure 2.7: Tee joint fillet weld (left) and flat butt weld (right)[57] ....................26
Figure 2.8: Initial grayscale images of the weld joints [52] ...............................26
Figure 2.9: Weld joints after pre-processing [52] ..............................................26
Figure 2.10: Weld joints after thresholding [52] ..............................................27
Figure 2.11: Weld joint detection method presented in [58] .............................28
Figure 2.12: Weld joint detection method presented in [59] .............................29
Figure 2.13: Weld joint detection using a ROI [60, 61] ..................................30
Figure 2.14: Local ROI [60] ..............................................................................30
Figure 2.15: ROI used to detect a fillet joint [63] ..............................................31
Figure 2.16: Online joint tracking using a ROI [64] ........................................31
Figure 2.17: Structured light and camera sensor [67] .....................................32
Figure 2.18: ServoRobot Laser Camera joint tracking system [57] ..................33
Figure 2.19: Epipolar geometry between two views .......................................35
Figure 2.20: A stereo image pair with epipolar lines and point correspondences[24] .................................................................36
Figure 2.21: Transformation from the image 1 to image 2 via a scene plane \( \pi \) ....37
using planar homography[24] ........................................................................37
Figure 2.22: Stereo rectified images [85] .......................................................37
Figure 2.23: Geometric camera error in triangulation [24] ..............................41
Figure 2.24: An example of the existing methods in [53] [63] and an example of the proposed method .............................................................47
Figure 3.1: Co-ordinate transformations ....................................................53
Figure 3.2: World frame set up .................................................................54
Figure 3.3: Precision pointer attached to the end of the weld torch ........................................54
Figure 3.4: Graphical representation of the Euler angles in Equation 3.15 ..................58
Figure 3.5: Automated camera calibration flowchart ..........................................................64
Figure 3.6: Proposed Calibration grid with 30mm × 30mm squares and 5mm diameter dots ..........................................................................................64
Figure 3.7: RGB colour image of calibration board ...............................................................65
Figure 3.8: RGB image after the red filter using Equation 3.50 ......................................66
Figure 3.9: Image after segmentation using Equation 3.52 ..............................................67
Figure 3.10: Red Square and dot with Harris corners .........................................................68
Figure 3.11: Blue squares and dots with Harris corners ................. .................................69
Figure 3.12: Calibration board boundary corners ...............................................................69
Figure 3.13: Example of a planar butt weld joint ...............................................................70
Figure 3.14: Planar butt weld joint detection overview ....................................................71
Figure 3.15: a) Grayscale image and b) the image after median filtering .................72
Figure 3.16: Pre-processing edge image .............................................................................73
Figure 3.17: Hough transform .............................................................................................74
Figure 3.18: Edge image with Hough lines (β=0.22) ........................................................76
Figure 3.19: Hough line edge segments .............................................................................77
Figure 3.20: Search windows ...............................................................................................77
Figure 3.21: Segmented image ...........................................................................................80
Figure 3.22: Edge identification in foreground image .......................................................81
Figure 3.23: Work piece boundary removed .....................................................................81
Figure 3.24: Image after small area removal .....................................................................83
Figure 3.25: Detected weld joint .........................................................................................83
Figure 3.26: Small areas not removed by threshold in Equation 3.44 .........................84
Figure 3.27: a) Weld joint with spurs b) after post processing .......................................84
Figure 3.28: Planar weld joint image matching overview .................................................86
Figure 3.29: Corner points for the left and the right image .............................................86
Figure 3.30: Overview of the combined fillet and butt weld joint detection method .89
Figure 3.31: Initial seed placement .....................................................................................91
Figure 3.32: Direction Probes ............................................................................................92
Figure 3.33: Movement example .......................................................................................94
Figure 3.34: Pseudo code for initial line growing .............................................................95
Figure 3.35: Initial region grow example ..........................................................96
Figure 3.36: Initial region growing results ..........................................................96
Figure 3.37: a) Initial region growing results after the direction change threshold b) remaining initial seed locations after the direction change threshold ..........................97
Figure 3.38: a) Initial seam lines after threshold b) corresponding seed points for the seam lines in a) .........................................................................................................101
Figure 3.39: Final seed location ............................................................................102
Figure 3.40: Weld joint gap ..................................................................................103
Figure 3.41: Edge tolerance ROI and edge detection ..........................................104
Figure 3.42: a) Hough lines b) parallel edge lines c) midpoint pixels used for tolerance ....................................................................................................................105
Figure 3.43: Seam line before end trimming .......................................................106
Figure 3.44: End trimming overview .....................................................................107
Figure 3.45: Canny edge detection .......................................................................108
Figure 3.46: Edge proximity image ......................................................................109
Figure 3.47: Trimmed weld seam .........................................................................111
Figure 3.48: Pseudo code for Final weld seam line growing .............................113
Figure 3.49: Multiple intersection example .......................................................115
Figure 4.1: Experimental setup ............................................................................119
Figure 4.2: Calibration setup ..............................................................................120
Figure 4.3: 30 images used for the left camera intrinsic parameter calibration ......121
Figure 4.4: 30 images used for the right camera intrinsic parameter calibration ....122
Figure 4.5: Robot link measurements [28] ..........................................................124
Figure 4.6: Robot axis locations [28] ..................................................................125
Figure 4.7: Hand-eye calibration images .............................................................127
Figure 4.8: Test points .........................................................................................130
Figure 4.9: Test position 1(left and right views) .................................................131
Figure 4.10: Test position 2 (left and right views) .............................................131
Figure 4.11: Test position 3 (left and right views) .............................................132
Figure 4.12: Test position 4 (left and right views) .............................................132
Figure 4.13: Minimised 3D Cartesian errors for test position 1 .......................133
Figure 4.14: Minimised 3D Cartesian errors for test position 2 .......................134
Figure 4.15: Minimised 3D Cartesian errors for test position 3 .......................135
Figure 4.16: Minimised 3D Cartesian errors for test position 4
Figure 4.17: Non-minimised 3D Cartesian errors for test position 1
Figure 4.18: Non-minimised 3D Cartesian errors for test position 2
Figure 4.19: Non-minimised 3D Cartesian errors for test position 3
Figure 4.20: Non-minimised 3D Cartesian errors for test position 4
Figure 4.21: Planar weld joint - case study 1
Figure 4.22: Planar weld joint - case study 2
Figure 4.23: Planar weld joint - case study 3
Figure 4.24: Experimental setup for planar weld joint detection
Figure 4.25: Weld joint detail for case study 1
Figure 4.26: Hough search lines - case study 1
Figure 4.27: Refined Hough lines - case study 1 (Equation 3.66)
Figure 4.28: Back segmentation - case study 1
Figure 4.29: Edge identification in foreground image - case study 1
Figure 4.30: Edge image after small area removal - case study 1 (Equation 3.67)
Figure 4.31: Boundary removal - case study 1
Figure 4.32: Final seam line - case study 1
Figure 4.33: Weld start close up - case study 1
Figure 4.34: First saw tooth peak close up - case study 1
Figure 4.35: Second saw tooth peak close up - case study 1
Figure 4.36: Weld end close up - case study 1
Figure 4.37: Weld joint detail for case study 2
Figure 4.38: Hough search lines - case study 2
Figure 4.39: Refined Hough lines for case study 2 (Equation 3.66)
Figure 4.40: Back segmentation - case study 2
Figure 4.41: Edge identification in foreground image - case study 2
Figure 4.42: Edge image after small area removal - case study 2 (Equation 3.67)
Figure 4.43: Boundary removal - case study 2
Figure 4.44: Final seam line - case study 2
Figure 4.45: Weld start close up - case study 2
Figure 4.46: Weld seam middle close up - case study 2
Figure 4.47: Weld end close up - case study 2
Figure 4.48: Weld joint detail for case study 3
Figure 4.49: Hough search lines - case study 3 ………………………………………157
Figure 4.50: Refined Hough lines - case study 3(Equation 3.66) …………………157
Figure 4.51: Back segmentation - case study 3 …………………………………………158
Figure 4.52: Edge identification in foreground image - case study 3………………158
Figure 4.53: Edge image after small area removal - case study 3 (Equation 3.67)…159
Figure 4.54: Boundary removal - case study 3 ………………………………………159
Figure 4.55: Final seam line - case study 3 …………………………………………160
Figure 4.56: Weld start close up - case study 3 ………………………………………160
Figure 4.57: First saddle point close up - case study 3 ……………………………161
Figure 4.58: saddle transition point close up - case study 3…………………161
Figure 4.59: Second saddle point close up - case study 3…………………………162
Figure 4.60: Weld end close up - case study 3 …………………………………………162
Figure 4.61: Weld joint detection comparison with aluminium on dark background …………………………………………………………………………………………………………………………164
Figure 4.62: Weld joint detection using method from [52] for case study 1 - seam line is not detected ………………………………………………………………………………165
Figure 4.63: Weld joint detection using method from [52] for case study 2 - seam line is not detected ………………………………………………………………………………165
Figure 4.64: Weld joint detection using method from [52] for case study 3 - seam line is not detected ………………………………………………………………………………166
Figure 4.65: localisation test markers - case study 1 ……………………………167
Figure 4.66: localisation test markers - case study 2 ……………………………167
Figure 4.67: localisation test markers - case study 3 ……………………………168
Figure 4.68: Harris feature points for case study 1. 179 putative matches with 37(21%) selected as inliers……………………………………………………………………………170
Figure 4.69: Harris feature points for case study 1. 248 putative matches with 36(15%) selected as inliers……………………………………………………………………………171
Figure 4.70: Harris feature points for case study 3. 133 putative matches with 12(9%) selected as inliers……………………………………………………………………………172
Figure 4.71: Example of an incorrect match from NCC …………………………174
Figure 4.72: Welding results for case study 1 using the proposed method – top view ………………………………………………………………………………………………………175
Figure 4.73: Welding results for case study 1 using the proposed method – side view ........................................................................................................176
Figure 4.74: Welding results for case study 2 using the proposed method – top view ........................................................................................................177
Figure 4.75: Welding results for case study 2 using the proposed method – side view ........................................................................................................177
Figure 4.76: Welding results for case study 3 using the proposed method – top view ........................................................................................................178
Figure 4.77: Welding results for case study 3 using the proposed method – side view ........................................................................................................179
Figure 4.78: The effects of welding variables on weld quality [57] ..................181
Figure 4.79: Aluminium fillet joint - case study 1 ........................................183
Figure 4.80: Mild steel tee fillet joint - case study 2 .......................................183
Figure 4.81: Mild steel channel to painted mild steel hollow section - case study 3184
Figure 4.82: Mild steel fillet joint – case study 4 ............................................184
Figure 4.83: Painted mild steel hollow section - case study 5 .......................185
Figure 4.84: Mild steel flat plate - case study 6 .............................................185
Figure 4.85: Initial seeds for the left and right view - case study 1 ..................186
Figure 4.86: Final seeds for the left and right view - case study 1 ..................187
Figure 4.87: Final seam line for the left and right view - case study 1 .............187
Figure 4.88: Close up of start and end points in the left view - case study 1 ......188
Figure 4.89: Close up of start and end points in the right view - case study 1 ....188
Figure 4.90: Initial seeds for the left and right view - case study 2 ...................189
Figure 4.91: Initial seeds for the left and right view - case study 2 ...................189
Figure 4.92: Final seam line for the left and right view - case study 2 ..............190
Figure 4.93: Close up of start and end points in the left view - case study 2 ......190
Figure 4.94: Close up of start and end points in the right view - case study 2 ....191
Figure 4.95: Initial seeds for the left and right view - case study 3 ...................192
Figure 4.96: Final seeds for the left and right view - case study 3 ...................192
Figure 4.97: Final seam line for the left and right view - case study 3 ..............193
Figure 4.98: Close up of start and end points in the left view - case study 3 .......193
Figure 4.99: Close up of start and end points in the right view - case study 3 ......194
Figure 4.100: Initial seeds for the left and right view - case study 4 ...............194
Figure 4.101: Final seeds for the left and right view - case study 4

Figure 4.102: Final seam line for the left and right view - case study 4

Figure 4.103: Close up of start and end points in the left view - case study 4

Figure 4.104: Close up of start and end points in the right view - case study 4

Figure 4.105: Initial seeds for the left and right view - case study 5

Figure 4.106: Final seeds for the left and right view - case study 5

Figure 4.107: Final seam line for the left and right view - case study 5

Figure 4.108: Close up of start and end points in the left view - case study 5

Figure 4.109: Close up of start and end points in the right view - case study 5

Figure 4.110: Initial seeds for the left and right view - case study 6

Figure 4.111: Final seeds for the left and right view - case study 6

Figure 4.112: Final seam line for the left and right view - case study 6

Figure 4.113: Close up of start and end points in the left view - case study 6

Figure 4.114: Close up of intermediate points in the left view - case study 6

Figure 4.115: Close up of start and end points in the right view - case study 6

Figure 4.116: Close up of intermediate points in the right view - case study 6

Figure 4.117: Localisation test markers - case study 1

Figure 4.118: Localisation test markers - case study 2

Figure 4.119: Localisation test markers - case study 3

Figure 4.120: Localisation test markers - case study 4

Figure 4.121: Localisation test markers - case study 5

Figure 4.122: Localisation test markers - case study 6

Figure 4.123: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 1

Figure 4.124: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 1

Figure 4.125: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 2

Figure 4.126: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 2

Figure 4.127: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 3
Figure 4.128: Reference pixel in the left image and the matching pixel in the right image for test point 2 – case study 3 .................................................................................210
Figure 4.129: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 4 ...................................................................................211
Figure 4.130: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 4 ...................................................................................211
Figure 4.131: Reference pixel (left image) and the matching pixel (right image) for test point 3 – case study 3 ...................................................................................212
Figure 4.132: Reference pixel (left image) and the matching pixel (right image) for test point 4 – case study 4 ...................................................................................212
Figure 4.133: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 5 ...................................................................................213
Figure 4.134: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 5 ...................................................................................213
Figure 4.135: Reference pixel (left image) and the matching pixel (right image) for test point 1 showing multiple intersections – case study 6 .........................214
Figure 4.136: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 6 ...................................................................................214
Figure 4.137: Reference pixel (left image) and the matching pixel (right image) for test point 3 – case study 6 ...................................................................................215
Figure 4.138: Reference pixel (left image) and the matching pixel (right image) for test point 4 – case study 6 ...................................................................................215
Figure 4.139: Welding results for case study 2 using the proposed method – front view .........................................................................................................................218
Figure 4.140: Welding results for case study 2 using the proposed method – side view .........................................................................................................................218
Figure 4.141: Welding results for case study 3 using the proposed method – front view .........................................................................................................................219
Figure 4.142: Welding results for case study 3 using the proposed method – side view .........................................................................................................................219
Figure 4.143: Welding results for case study 4 using the proposed method – front view .........................................................................................................................220
Figure 4.144: Welding results for case study 4 using the proposed method – close up
........................................................................................................................................220

Figure 4.145: Welding results for case study 5 using the proposed method – front view........................................................................................................................................221

Figure 4.146: Welding results for case study 5 using the proposed method – side view........................................................................................................................................221

Figure 4.147: Welding results for case study 6 using the proposed method – top view
........................................................................................................................................222

Figure 4.148: Welding results for case study 6 using the proposed method – side view........................................................................................................................................222

Figure 4.149: Close up of the “test point 2” weld using the proposed method – case study 6........................................................................................................................................223

Figure 4.150: Close up of the “test point 3” weld using the proposed method – case study 6........................................................................................................................................223
### List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMAW</td>
<td>Gas metal arc welding</td>
</tr>
<tr>
<td>GTAW</td>
<td>Gas tungsten arc welding</td>
</tr>
<tr>
<td>ROI</td>
<td>Region of interest</td>
</tr>
<tr>
<td>DH</td>
<td>Denavit-Hartenberg</td>
</tr>
<tr>
<td>CTWD</td>
<td>Contact tip to work distance</td>
</tr>
<tr>
<td>TCP</td>
<td>Tool centre point</td>
</tr>
<tr>
<td>RANSAC</td>
<td>Random sample consensus</td>
</tr>
<tr>
<td>SIFT</td>
<td>Scale invariant feature transform</td>
</tr>
<tr>
<td>NCC</td>
<td>Normalised cross correlation</td>
</tr>
<tr>
<td>SSD</td>
<td>Sum of the squared difference</td>
</tr>
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</table>
Abstract

At present, robotic welding is a rigid process which requires the robot to be taught by a human operator using teach and playback methods. A significant challenge for robotic welding to be widely adopted is the time taken to program the robot path for new parts. For example, in low to medium volume manufacturing and repair work, robotic welding is not always a viable option, as it can often be quicker and cheaper to weld the parts manually.

Some flexibility has been achieved in industry through offline programming software and vision systems that can be used to recognise a pre-taught part and shift the program to accommodate for any positional offsets. However these systems still require a human operator to program the robot path.

To achieve true flexibility and make robotic welding a viable option across the wider manufacturing industry, systems should be able to automatically identify the weld joints and then locate its position in the robot’s workspace. Computer vision can be used to achieve this kind of autonomy. However the welding environment presents unique challenges for computer vision. These challenges include poor contrast, reflections from metallic surfaces, and imperfections on the work piece such as rust, mill scale and scratches which are not consistent from part to part. The system should also be adaptable to a variety of surface finishes and base material such as paint, steel and aluminium.

This thesis develops an autonomous robotic arc welding system that is capable of detecting realistic weld joints and calculating their position in the robot workspace with minimal human interaction. This is accomplished using a pair of calibrated robot mounted stereo cameras combined with image processing algorithms. An automated calibration method for the robot and stereo vision system and image processing algorithms are developed in this thesis.

To obtain accurate positional information from the vision system, an automatic camera calibration method is integrated with simultaneous calibration of the welding robot and robot mounted stereo vision system. This provides accurate geometrical
transformations between the robot, cameras and the robot workspace which form the foundation of the computer vision algorithms for both the weld joint detection and localisation. The calibration algorithm is designed for economical and practical implementation. The automatic calibration not only allows for a faster initial calibration, but also reduces the machine down-time for any subsequent calibrations after an accidental collision or if the camera fixture is relocated. Unlike existing methods which require expensive 3D co-ordinate measuring devices or laser scanners, the optimised calibration method developed in this thesis is capable of achieving the sub-millimetre accuracy required for robotic arc welding using only the robot mounted stereo cameras, a mechanical pointer and a calibration board. This makes the proposed calibration method very practical, economical and easy to implement, hence making it highly desirable for industrial applications.

This thesis introduces new methods for autonomous identification for both butt and fillet weld joints regardless of the base material, surface finish and surface imperfections. The detection methods analyse the image from a global perspective and are able to identify the weld joint without prior knowledge of the shape of location of the weld joint in the image. The method to detect both butt and fillet joints introduces an approach for the detection of weld joints in realistic work pieces using a novel adaptive line growing technique developed in this thesis.

Image matching and triangulation of the weld joint is introduced using 2D homography for planar butt welds and an epipolar geometry based method for fillet welds. In the welding environment, traditional image matching is not reliable, as the images of weld joints typically contain similar shades of grey and are featureless and textureless. New image matching methods for weld joint matching are developed to provide reliable and accurate matching which is invariant to the environmental conditions of the welding environment.

The proposed algorithms are validated through experiments using an industrial welding robot in a realistic workshop environment. The results show that the methods introduced in this thesis can provide robust and accurate identification and localisation of weld joints which can be implemented in industry.
1. Introduction

Chapter 1   Introduction

1.1 Background

Welding is a fundamental and important process in manufacturing. It is considered to be a highly skilled profession and takes many years for a person to become fully qualified. Welding is also a physically demanding task and presents several challenges for safety such as hot environments, hazardous fumes and arc flash.

The demand for industrial robotics is increasing as the shortage of skilled labour and the demand to reduce manufacturing costs, particularly in developed countries, increases [1]. Robotic welders provide the solution for both competitive lean manufacturing and workplace safety. The International Labour Organisation reports that the demand for skilled labour will increase in the next decade as the global population ages [2]. A recent study shows that welding is critical to 90% of all durable goods produced in the United States, and there will be a significant demand for welders in the U.S. as the economy recovers from the global financial crises [3]. Similar reports commissioned by the Australian Government also identify shortages of skilled labour in several states [4, 5] where welding is vital to the mining and natural resource sectors. Therefore it is critical that robotic welding technology is developed to sustain production needs into the future.

At present, robotic welding is a rigid and structured process, and is generally purpose-built for mass production. Each new job must be programmed by human operators using teach and playback methods. It can take considerable amounts of time to program and commission new jobs. This makes robotic welding unsuitable for low to medium volume manufacturing, as it is often quicker to weld the parts manually. Furthermore, teach and playback programming requires highly repeatable parts with tight tolerances with expensive tooling to hold them in place. This can be justified in mass production; however the expense of designing new jigs and tooling as well as the costs associated with the lost production time for reprogramming
1. Introduction

makes the investment in robotic welding unjustifiable for low to medium volume production runs.

To make the benefits of robotic welding a viable option for these applications, it must become more flexible. The systems should be quickly and easily adapted to new parts. To achieve this kind of autonomous welding, the system would be required to automatically recognise the weld joints and accurately locate their position in the robot’s workspace. Computer vision systems can be used to detect the weld joints and provide a path to the robot to weld them automatically. They must also be versatile and robust enough to cope with the environmental and operational conditions of a welding workshop. For a computer vision system these environmental effects can include poor lighting conditions and imperfect work pieces that may be covered in rust, mill scale and scratches. While operationally, the vision system should be easy to set-up and calibrate. Re-calibration is inevitable as the camera system may be moved due to a collision, routine maintenance or if the camera fixture is relocated.

A roadmap for the development of a vision based autonomous robotic welding system includes five key technologies [6]:

1. Image segmentation and detection of the weld joint
2. Image processing and detection of the weld start point
3. Stereo matching algorithms for weld joint localisation
4. Autonomously guiding the robot to the weld start point
5. Real time control of joint tracking and weld pool dynamics

Steps 1-4 can be considered to be the most important to achieve the flexibility to overcome the deficiencies of manually programming the robot’s path. Once the weld joint has been detected and its real world co-ordinates accurately determined, a robot program can be created and sent directly to the robot controller. Real time joint tracking and weld pool control (step 5) is not usually an issue unless there is significant distortion of the work piece during welding or varying weld joint gaps. Typically, the distortion of the work piece and joint gaps can be overcome with
1. Introduction

clamps. The welding parameters are usually pre-determined by the welding engineer before operation to meet the required welding standard. Therefore they could be manually set by the operator prior to operation.

There are currently no commercially available weld joint detection methods capable of identifying weld joints without human operator involvement. In industry, current state of the art implementations of flexible robotic welding include vision systems such as the Fanuc’s iR Vision [7] and ServoRobot [8]. These are simple “look” and “shift” solutions. They are used to identify a pre-taught weld joint and then “shift” the manually pre-programmed path to accommodate any offsets in position. These vision systems are highly dependent on environmental lighting and part tolerances. If the lighting conditions change or if the part dimensions are outside of the taught specification, then these systems will fail. Offline simulation programs such as the Fanuc’s WeldPro [9] and ABB’s robot studio [10] can reduce setup time, however they still require significant human operator interaction and the programs taught in a virtual world will inevitably need to be “touched-up” when applied in the real world due to physical differences between the CAD model and the physical system layout.

Much of the research for weld joint detection has focused on Gas Tungsten Arc Welding (GTAW) of aluminium for butt weld joints. From a computer vision stand point, the high contrast between the bright aluminium work pieces and a dark background simplifies binary image segmentation. By comparison, there has been little work published on the detection of weld joints for Gas Metal Arc Welding (GMAW) of ferrous materials. The detection of weld joints for steel work pieces present unique challenges for computer vision. In a welding environment almost everything is made of steel including the work bench. This makes image segmentation more difficult for GMAW than GTAW as the work piece and the bench may be similar shades of grey. Furthermore, unlike simple butt-weld joints, fillet welds provide increased complexity. The thinner weld joint gaps and low contrast between the steel work pieces can make joint detection difficult.
1. Introduction

Currently there is no mature method for fillet or butt-weld joint detection in GMAW. Due to the large number of possible joint configurations, work piece materials and environmental impacts such as lighting conditions, weld joint detection and localisation cannot be solved by any single theory or method. While this remains unsolved, fully autonomous robotic arc welding cannot be achieved and will never be accepted in industry as a viable solution.

If the welding joint can be found in the image plane, the 2D pixel co-ordinates need to be transformed into 3D real world co-ordinates for robot path planning. Stereo vision can be used for weld joint localisation using triangulation. In computer vision, triangulation is the process of using the pixel co-ordinates of the same point in two or more images to determine their 3D real world location. Finding two or more matching points requires a process known as image matching. Weld joints do not contain unique feature points and can be considered as a repetitive texture. Similar to weld joint detection, stereo matching cannot be reliably solved with traditional methods due to the unique nature of the welding environment.

In general image processing technology has been developed for many years with many algorithms available for particular applications. However these applications are specific to a certain problem in image processing [11]. In particular for welding, image processing is difficult and requires the development of specialised image processing algorithms. To date there is no method that is capable of solving the requirements for autonomous robotic welding.

1.3 Aim of the Thesis

The main research aim of this thesis is to develop new computer vision methods for the reliable and accurate detection and localisation of weld joints in realistic robotic arc welding environments commonly encountered in industry. In particular this includes:
1. Introduction

1. Investigate methods that are presently available in computer vision for weld joint detection and localisation to identify current limitations and research gaps.

2. Develop computer vision methods for autonomous detection and localisation of realistic butt weld and fillet weld joints. The weld joint detection and localisation methods should be reliable and robust for use in industrial applications. The localisation of the weld joint should be within an acceptable accuracy for the majority of robotic arc welding applications.

3. Perform experiments using an industrial welding robot to verify the accuracy of the methods.

1.4 Contribution of the Thesis

The main contribution of this thesis is the introduction of computer vision methods for accurate and reliable detection and localisation of butt and fillet weld joints. The methods developed in this thesis provide a solution to the first 4 steps of the roadmap for the development of an autonomous robotic welding system identified in [6]. In particular these contributions are:

- An automatic calibration method is developed that can be used to calibrate the robot arm and the two robot mounted cameras simultaneously without the use of additional sensors such as external 3D measurement devices and laser scanners. The calibration is carried out using only the robot mounted cameras, a mechanical pointer and calibration board. Non-linear optimisation is used to minimise the absolute positioning errors between the robot and the world reference frame. The calculation of the 3D positions of the weld joints is achieved with stereo image matching.

- New weld joint detection methods are developed which are capable of detecting both butt and fillet weld joint configurations for multiple base materials without prior knowledge of the shape and location of the work
1. Introduction

piece in the image. The work pieces contain imperfections typically seen in
industrial applications such as rust, mill scale, paint and scratches

- A robot mounted eye-in-hand stereo vision system is used to detect the weld
  joint and then to calculate its 3D real world position using image matching
  methods developed in this thesis.

To demonstrate the validity and robustness of the proposed methods, experiments
are conducted in a realistic workshop environment using a standard industrial robot
and off the shelf USB cameras. The results show that the proposed methods can be
used to accurately and reliably detect and locate realistic welding joints for both butt
and fillet welds in a variety of shapes and base materials. The results will show that
the methods proposed in this thesis can produce the sub-millimetre 3D Cartesian
accuracy required by most robotic arc welding applications.

1.5 Publications

The list below contains the publications by the author during the research in this
thesis.

Journal

Localisation using Eye-in-Hand Stereo Vision for Robotic Arc Welding” in

Adaptive Line Growing Algorithm for Robotic Arc Welding” in Journal of
1. Introduction

**Journal (submitted)**


**Book Chapter**


**Conference Proceedings**


1. Introduction

1.6 Structure of the Thesis

The work presented is set out as follows: Chapter 2 will begin with a review of related literature to camera and robot calibration. This is followed by an extensive analysis of current vision based weld joint detection and localisation algorithms related to robotic arc welding.

Chapter 3 will detail the algorithms and methods developed in this thesis. In particular, the introduction of an automated calibration method for the robot, eye-in-hand stereo vision system and methods for the detection and localisation of both planar butt welds and non-planar fillet welds.

The experimental results and benchmarking against existing methods are given in Chapter 4. The analysis and benchmarking of the developed methods are verified using an industrial arc welding robot in a typical workshop environment.

The conclusions are given in Chapter 5. The conclusions will provide a summary of the research as well as a discussion of both the merits and limitations of proposed methods. A list of future work and suggested improvements are given following the conclusions.
Chapter 2  Literature Review

This chapter will begin with a review of the literature related to the calibration of cameras, robot manipulators and eye-in-hand vision system. A review of literature related to camera and robot calibration will provide the framework for the introduction of the topics related to stereo vision, eye-in-hand calibration and stereo matching. This is followed by a review of current methods for weld joint detection and localisation.

The extensive review of related literature in this chapter on the topics of robot and hand-eye calibration, weld joint detection and weld joint localisation will highlight crucial research gaps which are central to the development of the autonomous robotic arc welding system in this thesis. These research gaps are examined in detail and an overview of contributions of this thesis to fill these gaps is given.

2.1 Camera Calibration

2.1.1 Introduction

Camera Calibration is the process of calculating the intrinsic and extrinsic parameters of a camera. The intrinsic parameters include the lens focal length, lens distortion and pixel properties such as skewness and resolution. The extrinsic parameters describe the 3D position of the camera in space.

Camera calibration is a well-established area of research. Several well-known techniques have been developed and as a result, accurate camera calibration has been achieved [12-15]. The majority of the published methods involve the use of a calibration pattern. The calibration patterns are usually a checkerboard, coded markers, or circles in a grid pattern. Whichever pattern is used, the aim is to provide a set of feature points with known 3D positions. By obtaining the correspondences between the feature points in the 2D image plane and their 3D real world from multiple images, the camera parameters can be determined. An example of the
images obtained of a calibration board during calibration is shown below in Figure 2.1.

![Calibration board images taken during camera calibration](image)

*Figure 2.1: Calibration board images taken during camera calibration [14]*

### 2.1.2 Camera Model

The pinhole camera model is used in robotic and computer vision applications [13]. It models a feature point of an object in 3D space as a single ray of light projected through the aperture which is small enough to be considered a pinhole. The feature point is then projected onto the 2D image plane as a single point which is shown in Figure 2.2. Where \( P=(x,y,z) \) is the feature point in 3D space, \( \lambda \) is the camera’s focal length along the optical axis in the direction of the positive \( Z \) direction of camera’s reference frame and \((u,v)\) are the feature point projected on the image plane.

![Pinhole Camera Model](image)

*Figure 2.2: Pinhole Camera Model [16]*
2. Literature Review

Mathematically, the pinhole model is referred to as perspective projection. The projection of a point from the 3D Cartesian space to the 2D image space is represented by the following Equations

\[
\begin{bmatrix}
    u \\
    v \\
    1
\end{bmatrix} = \begin{bmatrix}
    X_w \\
    Y_w \\
    Z_w
\end{bmatrix}
\]

\[\begin{bmatrix}
    u \\
    v \\
    1
\end{bmatrix} = \begin{bmatrix}
    X_w \\
    Y_w \\
    Z_w
\end{bmatrix}
\]

\[\begin{bmatrix}
    X_w \\
    Y_w \\
    Z_w
\end{bmatrix} = \begin{bmatrix}
    X_c \\
    Y_c \\
    Z_c
\end{bmatrix}
\]

\[\begin{bmatrix}
    X_w \\
    Y_w \\
    Z_w
\end{bmatrix} = \begin{bmatrix}
    X_c \\
    Y_c \\
    Z_c
\end{bmatrix}
\]

where

- \(u, v\) The horizontal and vertical coordinate position of the feature point on the image plane \(p\).
- \(X_w, Y_w, Z_w\) The three coordinate positions along \(X\), \(Y\) and \(Z\) axes of the feature point in the world frame \(W\) which is attached to the calibration board.
- \(w\) Global scaling factor used in homogeneous representation.
- \(pK_c\) 3×4 transformation matrix from the camera frame \(C\), to the image plane \(p\) and is otherwise known as the camera intrinsic model. Where the subscript \(C\) is the camera frame and the superscript \(p\) is the image plane.
- \(CT_w\) 4×4 transformation matrix from the world frame \(W\), to the camera frame \(C\) and is otherwise known as the camera extrinsic model. Where the subscript \(W\) is the world frame and the superscript \(C\) is the camera frame.

The camera intrinsic model incorporates the cameras internal physical properties such as lens distortion and focal length. In most cases, this information can only be obtained through camera calibration. The definitions of the camera’s intrinsic properties are given in [12, 14] and are defined below.

A point \(P\) of an object given in the camera reference frame \(c\) is given by
2. Literature Review

\[
P_c = \begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix}
\]  

(2.3)

Let \(x_n\) and \(y_n\) be the normalised pinhole image projection of \(P_c\)

\[
\begin{bmatrix} x_n \\ y_n \end{bmatrix} = \begin{bmatrix} \frac{X_c}{Z_c} \\ \frac{Y_c}{Z_c} \end{bmatrix}
\]  

(2.4)

The perfect pinhole model describes a linear relationship between the image and camera plane, however due to the lens distortion this is not the case. The distorted projection points \(x_d\) and \(y_d\) are calculated in [14] as

\[
x_d = x_n + x_n [k_{r1} r^2 + k_{r2} (r^2)^2 + k_{r3} (r^2)^3] + 2 k_{r1} x_n y_n + k_{r2} (r^2 + 2 x_n^2)
\]  

(2.5)

\[
y_d = y_n + y_n [k_{r1} r^2 + k_{r2} (r^2)^2 + k_{r3} (r^2)^3] + k_{t1} (r^2 + 2 x_n^2) + 2 k_{t2} x_n y_n
\]  

(2.6)

\[
r^2 = x_n^2 + y_n^2
\]  

(2.7)

where \(k_{r1}, k_{r2}, k_{r3}\) are the coefficients of radial distortion and \(k_{t1}, k_{t2}\) are the coefficients of tangential distortion. In machine vision applications, the tangential distortion is not used as radial distortion is sufficient [13].

The pixel coordinates \(u\) and \(v\) on the image plane are then calculated as

\[
u = f_u (x_d + \alpha_c y_d) + u_0
\]  

(2.8)

\[
v = f_v y_d + v_0
\]  

(2.9)

where \(f_u, f_v\) are the focal length in pixels along the \(u\) and \(v\) direction respectively, \(u_0, v_0\) is the image centre co-ordinates in pixels and \(\alpha_c\) is the pixel skewness which is defined as the angle between the \(x\) and \(y\) axes of the camera.
2. Literature Review

In matrix form Equations 2.3 to 2.9 can be summarised as:

\[
\begin{bmatrix}
    u \\
    v \\
    1
\end{bmatrix} = \mathbf{p} \mathbf{K}_c \begin{bmatrix}
    x_d \\
    y_d \\
    1
\end{bmatrix}
\]

(2.10)

\[
\mathbf{p} \mathbf{K}_c = \begin{bmatrix}
    f_u & f_u \alpha_c & u_0 & 0 \\
    0 & f_v & v_0 & 0 \\
    0 & 0 & 1 & 0
\end{bmatrix}
\]

(2.11)

The camera extrinsic parameters describe the relative position of the camera frame with respect to the world frame as depicted in Figure 2.3. The world frame and are given by Equation 2.12:

\[
\mathbf{c}_T = \begin{bmatrix}
    \hat{x}_i & \hat{y}_i & \hat{z}_i & X_W \\
    \hat{x}_j & \hat{y}_j & \hat{z}_j & Y_W \\
    \hat{x}_k & \hat{y}_k & \hat{z}_k & Z_W \\
    0 & 0 & 0 & 1
\end{bmatrix} = \begin{bmatrix}
    \mathbf{c}_R & \mathbf{c}_P \\
    0 & 1
\end{bmatrix}
\]

(2.12)

where \(\mathbf{c}_R\) is the 3×3 orthogonal rotation matrix of \(\mathbf{c}_T\), which represents the relationship of the orientation of the world coordinate frame \(W\) to the camera frame \(C\). The three columns in the rotation matrix represent the orientation of the \(X_W\), \(Y_W\) and \(Z_W\) axes in the camera frame. \(\mathbf{c}_P\) is the 3×1 vector representing location of the origin of the world coordinate frame expressed in the camera frame.
2. Literature Review

![Projective transformation relationships](image)

**Figure 2.3: Projective transformation relationships**

2.1.3 *Automatic Camera Calibration*

One of the most time consuming stages of calibrating a vision system is the calibration of the individual cameras. The process of camera calibration can involve processing multiple images per camera. It is a repetitive and time consuming process. From this perspective, it makes sense to automate the camera calibration process. Furthermore during the calibration, the robot system would have to be taken off-line, therefore it is critical that the calibration be completed quickly so the robot can be put back into production with minimum down time, as a loss in productivity is undesirable and costly.

The calculation of the cameras intrinsic and extrinsic parameters can be achieved using well established methods [12, 13]. In these methods, the camera parameters are calculated using the known correspondence between the image plane and real world using feature points on a calibration object. However a challenge of camera calibration and computer vision is the automatic detection of the feature points on the calibration board. Environmental conditions such as lighting (i.e. shadows and bright spots) and background objects can make it difficult for a computer vision system to detect the feature points. The simple solution is to manually select the feature points but this is very time consuming and is not ideal for an automated system.
In [17, 18] grid detection algorithms are proposed for automatically detecting feature points on a checkerboard pattern. A self-adaptive threshold is used in [17] to eliminate the majority of false matches from background objects after the initial corner detection stage. The corner points are then evaluated by a symmetry constraint to return only the grid corner points. Similarly in [18] the architecture of the grid pattern is used to detect the corner points. False corner points such as those in the background are removed by using only the corner points that are at the intersection of lines projected along the edges of the grid squares.

Fiducial marker systems can also being used in camera calibration. Fiducial marker systems, such as the ARTag [19], provide an array of self-identifying patterns which can be detected by a computer vision system without any manual intervention. By automatically identifying the calibration pattern by way of coded markers, the grid corners can be easily extracted with a high degree of certainty as demonstrated in [20-22].

The extrinsic parameters of a camera are defined by a homogenous transformation matrix between the camera frame and the world co-ordinate frame. The world frame is defined by the calibration process and is usually attached to the calibration object [23, 24]. For stereo vision calibration, it is important to calibrate each camera using the same world co-ordinate system in order to determine the relative position between the cameras. The relative position of the cameras is required for the calculation of the epipolar geometry during triangulation [25]. Therefore the feature point detection algorithm must be able to determine the order of correspondence points to maintain a consistent world frame reference system for every calibration image. Typically, during camera calibration multiple images are taken of the calibration board from various positions and angles. Using a generic grid pattern it is difficult to identify individual corners, especially once the image is rotated greater than 90 degrees.

In this thesis a colour coded checkerboard pattern is proposed. The coloured grid squares are used to recognise and segment the calibration pattern from the
2. Literature Review

background and to identify a consistent world co-ordinate system for reliable stereo vision calibration.

2.2 Robot and Hand-Eye Calibration

2.2.1 Introduction

Camera calibration is only one step in the calibration of a vision guided robotic manipulator. For a vision system mounted to the robot end effector (eye-in-hand configuration), further calibration is required to find the geometric relationships between the camera system, the robotic manipulator and the object which is being manipulated or tracked. The calculation of the relationship between the robot and eye-in-hand vision system is referred to as robot hand-eye calibration.

An advantage of the eye-in-hand configuration when compared to a fixed camera system is that the cameras move with the robot. Since the cameras move with the robot, it is not as susceptible to occlusions. However the eye-in-hand configuration requires an intricate calibration process, as the geometrical relationship between the camera and the robot needs to be determined. It is often difficult to obtain a consistent and accurate calibration as it relies on the accuracy of the robot kinematic model and the camera calibration.

2.2.2 Robot Kinematic Model

The robot kinematic model is typically represented by its Denavit-Hartenberg (DH) parameters [26]. The DH parameters are used to find the geometrical transformations between the local co-ordinate frames of robot joints, and can be used to represent a manipulator made up of any combination of links and joints. The joints in an articulated robot are generally revolute and are assigned a local co-ordinate system with the z-axis pointing in the direction of rotation. The index number of the local reference frame for the \( n^{th} \) joint is assigned as \( n-1 \).

After all the joints are assigned a reference frame, additional DH parameters are established. The common normal between two consecutive z-axes, \( z_n \) and \( z_{n-1} \) is
2. Literature Review

represented by $a_n$ and is otherwise known as the joint offset. The joint angle representing rotation about the z-axis for the $n^{th}$ joint is $\alpha_n$. The angle between two consecutive z-axis, $z_{n-1}$ and $z_n$ about the $x_n$ axis is represented by $\alpha_n$ and is otherwise known as the joint angle offset. The last DH parameter is $d_n$ and represents the distance between the origin of the $(n-1)^{th}$ co-ordinate frame to the intersection of the $z_{n-1}$ with the $x_n$ axis along the $z_{n-1}$ axis.

Once the DH parameters have been established, the geometric transformation between consecutive joints can be calculated by

$${}^nT_{n+1} = \begin{bmatrix}
\cos \theta_{n+1} & -\sin \theta_{n+1} \cos \alpha_{n+1} & \sin \theta_{n+1} \sin \alpha_{n+1} & a_{n+1} \cos \theta_{n+1} \\
\sin \theta_{n+1} \cos \alpha_{n+1} & \cos \theta_{n+1} & -\sin \theta_{n+1} \sin \alpha_{n+1} & a_{n+1} \sin \theta_{n+1} \\
0 & \sin \alpha_{n+1} & \cos \alpha_{n+1} & d_{n+1} \\
0 & 0 & 0 & 1
\end{bmatrix}$$

(2.13)

where ${}^nT_{n+1}$ represents the homogenous transformation matrix from the $n+1$ joint frame with respect to the $n^{th}$ joint frame.

The DH parameters can then be used to calculate the homogeneous transformation from the robots wrist flange co-ordinate frame to the robots base co-ordinate frame.

$${}^R_T = {}^1T_2 {}^2T_3 {}^3T_4 {}^4T_5 {}^5T_F$$

(2.14)

where ${}^5T_F$ represents the transformation between the robots wrist flange frame with respect to the local co-ordinate frame attached to the $5^{th}$ joint and ${}^RT_1$ represents the transformation from the $1^{st}$ joint with respect to the robots base frame $R$.

As can be seen in Figure 2.4, the transformation matrix between the camera and the wrist flange ${}^RT_C$ is required to calculate the position of an object captured by the camera to be transferred to the robots base co-ordinate frame.
2. Literature Review

The calculation of a point relative to the robot’s base frame is required for path planning as industrial robot controllers require paths with position points relative to their base frame $R$. As depicted in Figure 2.4 this can be calculated by

$$^{R}T_{W} = ^{R}T_{F} ^{F}T_{C} ^{C}T_{W}$$ (2.15)

The robot path is calculated in the robot base co-ordinate frame $R$, which is referred to as the “world frame” by some robot manufacturers. However in some hand-eye calibration literature, the world frame is assigned to a convenient location away from the robot base frame [27]. In this Thesis, this naming convention is kept for generality, with the world frame attached to the calibration object.

There are many available methods for the calculation of the hand-eye transformation, which will be discussed in detail in the next section.
2. Literature Review

2.2.3 Classic Hand-Eye Calibration

The classic approach to hand-eye calibration is given in [28] and is commonly referred to as $AX=XB$, where $X$ is the hand-eye transformation, $A$ represents the robot kinematics and $B$ represents the camera extrinsic parameters. This method uses a camera mounted to the last link of the robot. The robot undergoes a series of $n$ movements. At each movement a picture is taken of a calibration object. At each robot position, the robot kinematic transformation $^RT_F$ and the camera extrinsic transformation $^CT_W$ are calculated and are given by $T_{6n}$ and $OBJ_n$ in Figure 2.5.

![Figure 2.5: Classic AX=XB [28]](image)

If the robot is moved from position $^RT_{F_n}$ to $^RT_{F_{n+1}}$, which moves the cameras relative to the fixed object from $^CT_{W_n}$ to $^CT_{W_{n+1}}$, then the following equation is obtained

$$^RT_{F_n}X^CT_{W_n} = ^RT_{F_{n+1}}X^CT_{W_{n+1}} \quad (2.16)$$

Simplifying Equation 2.16 let;

$$A_n = \left\{^RT_{F_{n+1}}\right\}^{-1}^RT_{F_n} \quad (2.17)$$
2. Literature Review

\[ B_n = e^{T_{Wn+1} \left\{ T_{Wn} \right\}^T} \]  

(2.18)

Therefore;

\[ A_n X = X B_n \]  

(2.19)

The method in [28] develops a method of obtaining a unique solution to Equation (2.19) based on geometric interpretations of the eigenvalues and eigenvectors of a rotational matrix. The robot is required to move to three positions which form two simultaneous equations which are solved separately for the rotation and translation components of the hand-eye matrix \( X \). The method is verified by computer simulation. The results show that an introduction of sensor noise in the robot kinematics and camera model produce a linear relationship between error in rotational components of \( A \) and \( B \) and the accuracy of \( X \). Therefore it can be said that hand-eye calibration is dependent on the accuracy of both the robot kinematic model and the camera model.

In [27] a method for simultaneous hand-eye and robot-world calibrated is proposed in the form of \( AX=ZB \), where \( X \) is the hand-eye transformation and \( Z \) is the robot-world transformation matrix \( ^WT \). This method, like \( AX=XB \) is susceptible to errors in the robot and cameras and requires the robot to be calibrated prior to hand-eye and robot-world calibration.

2.2.4 Robot Calibration

The DH parameters for the kinematic model of the robot are typically obtained from the nominal dimensions provided by the robot manufacturer. However, manufacturing tolerances can result in differences between the actual physical dimensions of the robot and the nominal dimensions. These differences can lead to inconsistent and unreliable hand-eye calibration. To determine the actual dimensions and improve the stability of hand-eye calibration, robot calibration is required.
2. Literature Review

Industrial robot manufacturers such as Fanuc and Motorman deliver their robots factory calibrated [29]. The aim of this calibration is to achieve repeatability through teach and playback programming and not for absolute position accuracy. For off-line programming, the robot must be calibrated so that the Cartesian positioning errors with respect to the robots base frame are reduced.

ABB’s Absolute Accuracy software [30] is able to achieve the positioning accuracy to approximately 0.5mm, providing the necessary accuracy to move from offline simulations to online production. Similarly Fanuc’s Vision Master [31] can be used to reduce the absolute positioning errors of the robot by recalibrating the robot kinematic model. However like all robot manufacturer branded calibration software it can only be used with their particular robots and is highly proprietary.

In [32] the authors solve robot calibration by using a hand mounted line-structured-light vision sensor consisting of a camera and laser projector acting as a virtual 7th link. The sensor is pointed at the centre of a precision sphere which is used as the calibration object. The laser camera is used to view a fixed point at the centre of the sphere from multiple robot configurations, at each configuration the hand to sensor transformation is calculated and the actual robot kinematic parameters are estimated using Multi-thread Particle Swarm Optimisation (MTPSO). The robot movements are continued until the measured and ground truth measurements converge.

Simultaneous robot and camera calibration is performed in [33]. This method utilises a hand mounted camera which observes a set of reference points on the calibration board. The 3D position of the reference points is calculated and compared to the ground truth data. A 3D co-ordinate measurement device was used to provide the ground truth data. The actual kinematic and camera model parameters are solved using the Levenberg-Marquardt algorithm to minimise the error against the known 3D co-ordinates of the calibration board. The results show that the 3D error improved significantly and that by combining the robot kinematic model and the camera parameters reduces the propagation of errors associated with multistage calibration, i.e. calibrating the robot and the camera separately.
2. Literature Review

In [34] a laser tool is attached to the end-effector of the robot which acts as a virtual 7th link of the robot. The laser point is observed by a camera system by directing it onto an arbitrary point on a transparent plane forming a closed loop kinematic chain. Since the position of the plane and the robot kinematics are known, an estimation of the laser point can be obtained. The robot is then moved around the laser point by adjusting the joint angles. A PID controller is then implemented to finely adjust the laser point back to its nominal position observed by the camera. By comparing the actual position of the laser point and the parameters used to calculate the joint configurations in the PID controller, the true DH parameters are found using non-linear minimisation. The experiments achieved Cartesian position accuracy approximately five times better than the un-calibrated robot.

The calibration of a robotic manipulator typically involves constraining the end-effector to a known position which is referred to as closed loop calibration. Alternatively the robot can be moved around a measuring device which can detect the position errors to high accuracies such as lasers and 3D co-ordinate measurement devices, which is referred to as open loop calibration [35-38].

2.2.5 Optimised Hand-Eye Calibration

The optimised approach to hand-eye calibration can involve combining the hand-eye transformation and camera model into a single objective function. Non-linear optimisation then allows for simultaneous camera and hand-eye calibration. The aim of simultaneous calibration is to eliminate propagation errors that arise from multistage calibration. The initial estimates for the camera parameters and hand-eye transformation are obtained using well established methods.

In [39] a combined stereo camera and hand-eye calibration algorithm is proposed. The method involves capturing a set of images of a static 2D calibration board which is used to estimate the cameras intrinsic parameters. The initial estimate for the hand-eye transformation is calculated using [40] and then robot-world transformation is
solved using the mean of Equation (2.15) over \( n \) robot positions. All the parameters are then combined into a single objective function. The parameters are solved using the Levenberg-Marquardt algorithm to minimise the geometric error against the known 3D co-ordinates of the calibration board. The method is validated through experiments using a 6-axis industrial robot fitted with an eye-in-hand stereo vision system. The 3D position error was then calculated by comparing the calculated position of several points on the calibration object using the method in [39] and comparing them to the values obtained by using the robot to touch the same points using a precision pointer. The experimental results show that this method is capable of achieving 3D Cartesian accuracy to within 2mm which is suitable for the surgical bone cutting applications for which the method is intended. Similarly in [41] camera and hand-eye calibration are combined with the reported accuracy to within 4.5 pixels. Both the methods in [39, 41] are not accurate enough for robotic arc welding.

The research in [42] extends the work of [27, 43] by providing optimal solutions to the \( AX=XB \) and \( AX=ZB \) methods. A physical geometry based error metric and automatic weighting factor is introduced into the optimisation models. The results are validated by simulated models. The comparisons against well-known optimisation methods show improved performance, however it is not validated with real world results.

In [44] a linear convex optimisation method is introduced. The proposed method is compared against traditional nonlinear hand-eye optimisation as [39, 43, 45, 46]. The main advantage is that it does not require accurate initialisation of the optimisation parameters. The rotation and translation errors of the proposed method marginally better than the methods it is compared too.

The required 3D Cartesian accuracy for GMAW welding robot is less than the diameter of the welding wire. This means that for an electrode of 1.2mm the error should be at least ±1mm from the centre of the joint i.e. the \( X \) and \( Y \) direction. The accuracy of \( Z \) measurement, which represents the contact tip to work distance (CTWD) can be slightly greater by a few millimetres. For modern inverter welding power sources, small variations in the CTWD can be accounted for while welding
using the inbuilt adaptive welding waveforms. Large variations in CTWD can affect
the welding arc characteristics and results in a poor weld finish; however deviations
by a few millimetres in CTWD would not greatly affect the quality of the result. The
Lincoln Electric Pulse [47], RapidArc [48] and Power Mode [49] waveforms utilise
an adaptive control loop to which varies the welding output according to changes in
the CTWD [47].

The effects of tool centre point (TCP) calibration on the accuracy of the vision
system are studied in [50]. For an industrial robot without a gripper or welding torch,
the TCP coincides with the origin of the robots wrist flange co-ordinate frame. Once
a welding torch is attached to the wrist, the TCP needs to be recalibrated to coincide
with the welding torch tip. This can be achieved using the inbuilt software provided
by the robot manufacturer [29]. The model analysis demonstrates that the accuracy of
the TCP is related to robot calibration. The results show a direct correlation to
absolute positioning error of the robot and TCP calibration. An error model is also
proposed to determine the optimal height of image capture to obtain accurate 3D co-
ordinates in the image. Then an optimum height can be selected to achieve sub-
millimetre accuracy

2.3 Weld Joint Detection

2.3.1 Introduction

Currently, weld joint detection methods can be grouped into two categories. The
first are the global search methods where no prior information exists about the
location of the weld joint in the image. The second are the local weld joint search
methods which utilise either a predefined region of interest (ROI) or structured light
sensors. The local methods can be used for both offline detection of the weld joint
and online joint tracking during welding.

The detection of weld joints using computer vision involves many challenges
unique to the welding environment. As stated in [11] it is fair to argue that image
processing technology has been developed for many years with many algorithms
available for particular applications. These applications are specific to a certain problem in image processing. In particular for welding, image processing can be difficult due to reflective metallic surfaces, low contrast between the steel work piece and work bench, and imperfections such as scratches, rust and mill scale on the work piece can interfere with edge detection. Therefore, specific algorithms need to be developed for weld joint detection.

2.3.2 Global Weld Joint Detection

Much of the research using the global search methods have focused on GTAW of aluminium [11, 51-56]. The methods presented in these papers address the detection of planar and non-planar weld joints for butt-weld configurations. The butt and fillet welds are two common welds and are shown in Figure 2.6 and Figure 2.7.

Figure 2.6: Types of butt and fillet weld joint configurations[57]
2. Literature Review

Figure 2.7: Tee joint fillet weld (left) and flat butt weld (right) [57]

In [52] a weld joint detection algorithm is presented for identifying the initial starting point for butt welds for GTAW. The pre-processing stage includes smoothing, sharpening and region segmentation. Region segmentation is achieved using an automatic binary threshold. A pixel area threshold is then applied to remove any unwanted regions caused by reflections or scratches. The process is shown below in Figures 2.8, 2.9 and 2.10. The start and the end points of the weld joint are then found by detecting two adjacent corners by using a corner detection algorithm. The corners of the starting points are distinguished from those in the weld contour by comparing the direction of the contours.

Figure 2.8: Initial grayscale images of the weld joints [52]

Figure 2.9: Weld joints after pre-processing [52]
Similarly in [51], the detection of various shaped butt weld joints is achieved using an adaptive binary threshold. The weld joint is then found using a modified K-cosine method for corner detection. In both [51, 52] and in [53, 54] the work piece is segmented from the background using a binary threshold leaving the weld joint clearly visible. While the results show that these methods are accurate and effective they cannot be used in all situations. It can be seen that there is high contrast between the bright aluminium work piece and the darker background. This contrast makes it easier to segment the image using a binary threshold. By comparison, weld joint detection using computer vision for mild steel GMAW is more difficult. This is because there is less contrast between the mild steel work pieces which makes background segmentation more difficult. This is because the background which is usually a steel workbench is similar in colour to the steel work piece.

The detection of butt weld joints for both GTAW and GMAW is researched in [58]. A weld joint identification method is introduced for simultaneously segmenting the image and detecting the weld joint. This is achieved by comparing an image of the background without the work piece to another image taken from the same position with the work piece present as shown in Figure 2.11(a) and (b). The two images are compared using degrees of gray similarity to subtract the background and leave only the work piece in the image (c). Filters (d) and thresholds (e-f) are then used to eliminate the remaining noisy areas from the subtraction process. The disadvantage of this method is that it requires the setup of multiple shots for each part. For an automated welding process it would be more convenient to capture a single image to reduce setup and cycle time. This method is also used in [55] to
2. Literature Review

detect the weld joint. A corner detection method is then developed to find the weld start point.

![Figure 2.1: Weld joint detection using the method presented in [58]](image)

The global detection of fillet weld joints is investigated in [59]. It is observed that the pixel intensities of the weld joint are much darker than the surrounding pixels. Based on this, a pixel intensity threshold for the weld joint is manually selected for image segmentation. All pixels that are brighter than the threshold are set to white. The image segmentation is followed by edge detection and then a filter is used to remove any remaining edges that do not belong to the weld joint. The process is shown in Figure 2.12. It can be seen in Figure 2.12, the addition of white boards on table at the weld joint end positions assists in providing the necessary contrast between the table and work piece for effective segmentation.
2. Literature Review

![Weld joint detection using the method presented in [59]](image)

Figure 2.12: Weld joint detection using the method presented in [59]

In practice it is not always possible to improve the contrast between the work piece and the welding bench by placing coloured boards between them. Electrical conductivity between the work piece and bench is required to provide an effective earth for the welding current. Therefore it is not possible to paint the workbench or place the work piece on nonconductive coloured materials. The image processing algorithm must be capable of detecting the weld joint regardless of the background to foreground contrast.

2.3.3 Local Weld Joint Detection

To overcome the limitations of contrast, complex backgrounds and reflective surfaces, a predefined analysis window called a region of interest (ROI) can be used. The ROI is usually placed at the centre of the image. The work piece and robot are then positioned so that only the weld joint is visible within this window.

In [60, 61] a ROI weld joint detection algorithm is develop for planer and non-planer butt welds. The ROI is set in the centre of the image as shown in Figure 2.13.
2. Literature Review

Figure 2.13: Weld joint detection using a ROI [60, 61]

The pre-processing stage involves locating the weld joint within the ROI. This is achieved by creating a local binary image of the ROI and then selecting the two longest parallel edges as shown in Figure 2.13(c). Once the weld joint has been located, smaller predefined ROI windows move along the direction of the weld joint until the two ends of the joint are found (Figure 2.14). The end points are identified using a corner detection algorithm. However this method will fail if there are any discontinuities in the edge segments due to strong lighting reflections or scratches.

Figure 2.14: Local ROI [60]

Similarly in [62] a ROI is used to determine a pixel intensity threshold to segment the background and the work piece. The weld joint is found using the method in [51] The ROI method can also be used for fillet weld joint detection [63] and is shown in Figure 2.15. The local ROI image is converted to a binary edge image, and the weld joint selected as the longest continuous edge segment.
2. Literature Review

![ROI used to detect a fillet joint](image)

**Figure 2.15: ROI used to detect a fillet joint** [63]

The ROI is also used for online tracking of the weld joint during the welding process by visual servoing [16]. Special welding lenses allow the camera to see the joint and the end of the welding wire in the presence of the arc flash. The ROI is placed at the front of the torch in the direction of welding as shown in Figure 2.16. The joint detection typically consists of smoothing, edge detection and edge recognition [64-68].

![Online joint tracking using a ROI](image)

**Figure 2.16: Online joint tracking using a ROI** [64].

The use of a ROI for weld joint detection assumes that the joint can be positioned at the centre of the image. From a practical standpoint it may not always be possible to position the robot and/or vision system this way. The geometry of the part and the tooling or jigs can restrict access. Secondly it assumes that the weld joint will be large in comparison to the size of the ROI. The size of the ROI is also critical to the
effectiveness of the edge detection. If the window is too large, background objects may interfere with detection. The accuracy and consistency of the binary edge image can also be affected by the grayscale intensity distribution of the image [61]. The size of the window must then be selected by an operator on a case by case basis. For an automated system this is not desirable.

A vision system with structured lighting may also be used for weld joint detection and online tracking [69-71]. The structured lighting sensors are usually a laser stripe emitter which projects a line across the weld joint as shown in Figure 2.17. The laser stripe is detected by a camera and the weld joint is found by analysing the shape of the stripe as it intersects the joint.

There are several laser camera systems available in industry such as ServoRobot [8], however these sensors are very expensive and can cost almost as much as the robot. The implementation of cameras and lasers for online weld joint detection has limited applications. This configuration will require the camera and laser emitter to be mounted close to the end of the welding torch which restricts access to welds. Secondly the camera and/or laser must be able to detect the weld joint ahead of the welding torch as shown in Figure 2.18. This means that the robot pose and welding torch angle are restricted which reduces the working envelope of the robot. In the
2. Literature Review

case of butt weld joint detection, there must be a gap of at least 0.2mm between the parts for the laser emitter to detect the joint. If there is no gap, then the joint will not be detected.

Figure 2.18: ServoRobot Laser Camera joint tracking system [57]

2.4 Weld Joint Localisation

2.4.1 Introduction

For a vision based autonomous welding system, stereo vision can be used to calculate the 3D co-ordinates of the weld joint. This can be achieved using triangulation. In computer vision, triangulation is the process of using the pixel co-ordinates of the same point in two or more images to determine their 3D location. The matching of points requires a process known as image matching. In particular for a stereo vision system this is referred to as stereo matching.

Stereo matching is a well-researched area and many methods have been developed for different scenarios. These include epipolar geometry and pixel
intensity based methods such as cross correlation [72], feature point matching such as Scale Invariant Feature Transform (SIFT) [73, 74] and planar homography estimation using Random Sample Consensus (RANSAC) [25, 75].

Due to specific challenges of the welding environment, stereo matching is not a trivial process. Typically the image regions around the weld joints can be considered featureless as the weld joint is a uniform groove between two metal components. They also have uniform texture due to monotone steel surfaces which are mostly grey in colour. The reflections off the steel surfaces together with ambient lighting conditions greatly affect the contrast and pixel intensity between the left and right views.

2.4.2 Epipolar Geometry

Epipolar geometry describes the relation between right and left projections of a common feature point seen in both images. The epipolar geometry is reliant on the cameras intrinsic parameters and the relative position of the camera/s between the two views. For stereo matching, epipolar geometry is particularly useful because given a point in the first image \( x_1 \) the corresponding point \( x_2 \) in the second image is constrained to the epipolar line \( l_2 \) and vice versa as shown in Figure 2.19. It can also be seen that the corresponding image points \( x_1 \) and \( x_2 \), the feature point \( X \) and camera centres lie on a common plane which is known as the epipolar plane \( \pi \).
2. Literature Review

Figure 2.19: Epipolar geometry between two views

The fundamental matrix $F$ is a $3 \times 3$ matrix which incorporates the camera/s intrinsic parameters and the relative position of the camera/s. It is used to calculate the epipolar geometry between two views. The properties of fundamental matrix and epipolar geometry are derived in [25]. The equations relevant to stereo matching are given below.

For a calibrated stereo vision system, the fundamental matrix can be calculated as

$$F = \left(K_{c1}^{-1}\right)^{\top}S\left(K_{c2}\right)^{-1}\left(K_{c2}^{-1}\right)^{\top}$$  \hspace{1cm} (2.20)

where $R$ is the $3 \times 3$ orthogonal matrix which describes relative rotation from camera 2($c_2$) to camera 1($c_1$), $K_{c1}$ and $K_{c2}$ are the intrinsic parameter matrices of camera 2 and camera 1 respectively which are derived in Section 2.1 and $S$ is the skew symmetric matrix of the relative translation $(t_x, t_y, t_z)$ from camera 2 to camera 1 and is given by
2. Literature Review

\[
S = \begin{bmatrix}
0 & -t_x & t_y \\
t_z & 0 & -t_x \\
-t_y & t_x & 0
\end{bmatrix}
\]

(2.21)

The epipolar line in the second image generated by the pixel co-ordinates of the feature point in the first image is calculated as

\[
l_2 = Fx_1
\]

(2.22)

Equation 2.22 reduces the search for corresponding image co-ordinates \(x_1 \leftrightarrow x_2\) which relate to the feature point \(X\) from the entire image to a single line as shown in Figure 2.20. Additional search criteria still need to be implemented to determine the matching points.

![Figure 2.20: A stereo image pair with epipolar lines and point correspondences][25]

2.4.3 Planar Homography

Corresponding image co-ordinates viewed on the same plane in a pair of images can be related by a planar homography as shown in Figure 2.21. In projective geometry, 2D homography transformation is defined as a matrix that maps image points from the same plane in two images as defined by

\[
x_{2i} = H_{\pi} x_{li}
\]

(2.23)
2. Literature Review

where \( x_{1i} = (u_{1i}, v_{1i}, w_{1i})^T \) and \( x_{2i} = (u_{2i}, v_{2i}, w_{2i})^T \) are corresponding homogenous pixel co-ordinates in image 1 and 2, the superscript \( T \) is the matrix transpose and \( H_\pi \) is the homography transformation matrix that maps \( x_{1i} \) to \( x_{2i} \) via the plane \( \pi \)

![Diagram of Transformation from Image 1 to Image 2](image)

**Figure 2.21: Transformation from the image 1 to image 2 via a scene plane \( \pi \) using planar homography[25]**

A full derivation for the solution of \( H \) can be found in [25]. An overview in context to stereo matching is given here.

The expression in Equation 2.23 forms three homogenous vectors which have the same direction but may vary in magnitude up to a non-zero scale factor. Therefore by expressing Equation 2.23 as a cross product, a linear solution for \( H \) can be formed

\[
x_{2i} \times Hx_{1i} = 0
\]  
(2.24)

Let the \( j^{th} \) row of the matrix \( H \) be denoted by \( h^j \) then

\[
Hx_{1i} = \begin{pmatrix} h^1 x_{1i} \\ h^2 x_{1i} \\ h^3 x_{1i} \end{pmatrix}
\]  
(2.25)

Re-arranging Equation 2.24 and substituting \( x_{2i} = (u_{2i}, v_{2i}, w_{2i})^T \), Equation 2.24 becomes

37
2. Literature Review

\[
\begin{bmatrix}
0^T & -w_{2i}x_{li}^T & v_{2i}x_{li}^T \\
-w_{2i}x_{li}^T & 0^T & -u_{2i}x_{li}^T \\
v_{2i}x_{li}^T & u_{2i}x_{li}^T & 0^T
\end{bmatrix}
\begin{bmatrix}
h_1^T \\
h_2^T \\
h_3^T
\end{bmatrix} = 0
\] (2.26)

Equation 2.26 has the form \( Ah = 0 \), where \( A \) is a 3x9 matrix and \( h \) is a 3x3 matrix. Of the three equations in Equation 2.26, only 2 are linearly independent as the third is defined up to scale. Equation 2.26 is then commonly written as

\[
\begin{bmatrix}
0^T & -w_{2i}x_{li}^T & v_{2i}x_{li}^T \\
-w_{2i}x_{li}^T & 0^T & -u_{2i}x_{li}^T \\
v_{2i}x_{li}^T & u_{2i}x_{li}^T & 0^T
\end{bmatrix}
\begin{bmatrix}
h_1^T \\
h_2^T \\
h_3^T
\end{bmatrix} = 0
\] (2.27)

Equation 2.27 still has the form \( Ah = 0 \), where \( A \) is now a 2x9 matrix. Since \( H \) is only defined up to scale, it has 8 degrees of freedom. Each set of correspondences provides two equations, and therefore at least 4 sets of non-co-linear correspondences are required to constrain the 8 degrees of freedom. Singular Value Decomposition can be then used to solve for the transformation matrix \( H \).

The autonomous calculation of the homography can be difficult. As mentioned it requires at least four corresponding points in the two images which are on the same plane. Therefore it is not only a stereo matching problem, but also a plane fitting problem. The mature process for homography estimation utilises RANSAC for the so called “robust homography estimation” method [25, 76].

The general process starts by detecting feature points in the two images using methods such as Harris Corners [77, 78] or SIFT [74, 79] descriptors. For each feature point in the first image, its corresponding point in the second is matched. The matching can be achieved using a particular matching algorithm such as cross correlation or SIFT. Over a number of iterations, random samples of four correspondences are chosen and the homography calculated. Each of correspondences are considered to be an “inlier” or and “outlier” depending on their concurrence with the calculated homography. Correspondences are statistically chosen to comply as an inlier if they are within a certain cost function. The cost
function is usually the distance between the actual pixel location and the re-projected location using the estimated homography $H'$ as given by

$$d(x_1, H'x_2) = |x_1 - H'x_2|$$ \hspace{1cm} (2.28)

The correspondences that comply with the cost function are considered to be “inliers” where the distance is less than a threshold $T_{\text{pixels}}$ such that

$$d(x_1, H'x_2) < T_{\text{pixels}}$$ \hspace{1cm} (2.29)

After all the iterations are completed, the iteration with the largest number of inliers is chosen and the final homography matrix is calculated using the best inliers.

For stereo matching and triangulation, it is important to segment the image so that homography is only estimated for the regions or features which are required. In particular homography estimation for the stereo matching and triangulation of a welding joint can be difficult. Firstly it is difficult to obtain the necessary correspondences for the particular plane of the weld joint. Even after the work piece has been segmented, e.g., Figure 2.10, it can be difficult to obtain reliable matches as there may not be enough distinct feature points for SIFT or cross correlation to be effective. Also if the weld joint is not on a single plane, then each plane must be identified and its homography estimated.

2.4.4 Pixel Intensity Matching

As discussed in Section 2.4.2, the epipolar line reduces the search for a matching point to a single line. One of the most researched areas for stereo matching using the epipolar line constraint is cross correlation [72].

A template window is formed around a reference pixel in the first image. The matching pixel is then searched for along the corresponding epipolar line in the other image using localised search windows. The matching criterion is typically based on comparing the pixel intensity profiles of the template window and the matching
window. Because the matching is based on pixel intensity profiles, this kind of matching will only be reliable when the windows in both images have a distinct pixel intensity profile. It is well documented that cross correlation is not effective for textureless regions, rotated images, repetitive patterns and features and reflections [80].

Typical cross correlation algorithms are sum of squared difference (SSD), Sum of the absolute difference (SAD) and normalised cross correlation (NCC) [72, 81-84].

NCC is considered to be one of the best cross correlation methods as it is more reliable when there are variations in pixel intensities of the same regions due to lighting or contrast changes between stereo images. The general formulation for NCC for stereo matching can be given as

\[
C = \frac{\sum_{i=-w}^{w} \sum_{j=-w}^{w} (I_1(u_1 + i, v_1 + j) - \bar{I}_1) (I_2(u_2 + i, v_2 + j) - \bar{I}_2)}{\sqrt{\sum_{i=-w}^{w} \sum_{j=-w}^{w} (I_1(u_1 + i, v_1 + j) - \bar{I}_1)^2 (I_2(u_2 + i, v_2 + j) - \bar{I}_2)^2}}
\]

where \(C\) is the correlation score, \(I_1\) and \(I_2\) are the stereo images from camera 1 and camera 2. \(\bar{I}_1\) and \(\bar{I}_2\) are the mean of the images. \(I_1(u_1,v_1)\) and \(I_2(u_2,v_2)\) is the pixel location of the reference point in \(I_1\) and the point which is being searched in \(I_2\). \(w\) is the correlation window which has a width \(\times\) height of \(2w+1\) pixels. The matching pixel is therefore located at the centre of the search window in the second image which has the maximum correlation with the template window in the first image. A correlation score of 1 is a perfect match.

Cross correlation can be improved by using rectified stereo images [85, 86]. Stereo rectification aligns the horizontal axis of the images so that the epipolar lines are reduced to horizontal scan lines as shown in Figure 2.22. Aligning the horizontal axes simplifies the search for the \(v\)-axis co-ordinate of the matching pixel. This also improves the reliability of a match to be found when there is some rotation between
images. This is because the pixel intensity profile of the template window and the match windows now seen from the same perspective.

![Stereo rectified images](image)

Figure 2.22: Stereo rectified images [85]

### 2.4.5 Triangulation

In computer vision, triangulation is used to calculate the 3D real world position of a feature point in an image. It requires that the image co-ordinates of the feature point are known in two or more images and calculating where the projected rays intersect in space.

The simple linear triangulation method can be solved by combining Equation 2.1 for two or more views. For two views, the 3D world co-ordinates can be solved using the following method from [25]
2. Literature Review

\[
\begin{bmatrix}
  u_1 M_{C1}^3 - M_{C1}^1 \\
v_1 M_{C1}^3 - M_{C1}^2 \\
u_2 M_{C2}^3 - M_{C2}^1 \\
v_2 M_{C2}^3 - M_{C2}^2
\end{bmatrix}
\begin{bmatrix}
  X_w \\
  Y_w \\
  Z_w
\end{bmatrix} = 0
\]  

(2.31)

where \((u_1, v_1)\) and \((u_2, v_2)\) are the image points of the feature point in image 1 and image 2, respectively, \(M_{C1}\) and \(M_{C2}\) are the camera projection matrices for camera 1 and 2 which is given by Equation 2.2, and \((X_w, Y_w, Z_w)\) are the 3D co-ordinates of the feature point in the world co-ordinate frame. It can be seen that Equation 2.31 has the form \(AX=0\) which be solved using Singular Value Decomposition or least squares.

However, linear triangulation is not the optimal solution due to the presence of noise in real world applications. For cameras, this noise can be associated with geometric error introduced by lens distortion and errors associated with camera calibration. For a linear system, the rays from the image feature points will intersect in space and obey the epipolar constraint. However in the presence of noise, the rays may not intersect which is shown in Figure 2.23.

![Figure 2.23: Geometric camera error in triangulation [25]](image)
2. Literature Review

In [87] a non-iterative optimisation algorithm is introduced to minimise the geometric error by using the epipolar constraint in the cost function. However for a calibrated stereo vision system, the camera model can be made linear by removing the effects of lens distortion as discussed in [88].

From Equations 2.8 and 2.9 if the co-efficients of lens distortion are known, then the ideal undistorted image co-ordinates can be calculated. Let \((u, v)\) be the ideal (distortion free) pixel co-ordinates, and \((\bar{u}, \bar{v})\) be the observed pixel co-ordinates. The corresponding normalized image coordinates are given by \((x_d, y_d)\). The distorted pixel co-ordinates are related to the ideal co-ordinates by

\[
\bar{u} = u + (u-u_0)[k_1(x_d^2 + y_d^2) + k_2(x_d^2 + y_d^2)^2] \quad (2.32)
\]

\[
\bar{v} = v + (v-v_0)[k_1(x_d^2 + y_d^2) + k_2(x_d^2 + y_d^2)^2] \quad (2.33)
\]

where \(k_1\) and \(k_2\) are the coefficients of radial distortion determined in the camera calibration stage. Rearranging Equations 2.32 and 2.33 to solve for \((u,v)\) gives

\[
u = \frac{\bar{u} + u_0k_1(x_d^2 + y_d^2) + u_0k_2(x_d^2 + y_d^2)^2}{[1 + k_1(x_d^2 + y_d^2) + k_2(x_d^2 + y_d^2)^2]} \quad (2.34)
\]

\[
v = \frac{\bar{v} + v_0k_1(x_d^2 + y_d^2) + v_0k_2(x_d^2 + y_d^2)^2}{[1 + k_1(x_d^2 + y_d^2) + k_2(x_d^2 + y_d^2)^2]} \quad (2.35)
\]

2.4.6 Weld Joint Localisation

If the welding seam is extracted as a feature in both the left and right views, then finding the matching points is simplified by using the intersection of the epipolar line with the weld seam. This method has an additional benefit that it does not require rectified images, which not only simplifies the matching process but reduces the computation time. It is also independent of pixel intensity comparisons.
2. Literature Review

In [53] an eye-in-hand vision system is used for weld joint detection and localisation. The joint is identified in a pair of stereo images by using an improved sub-pixel edge identification algorithm. The matching points are found by calculating the intersection of the epipolar line produced by the seam line points in one image and the seam line in the other. Experimental results show that the maximum localisation error is less than 4.5mm for fillet joints and 3mm for flat butt welds. Neither of which are acceptable for robotic arc welding as they do not meet the required accuracy as discussed in Section 2.2.5.

Similarly in [59, 63] the matching points are found using the intersection of the epipolar line and the seam line. The results of [59] show an average error of 1.96mm and less than 1mm in [63]. This method of stereo matching is fairly trivial when the epipolar line and seam line intersect at only one point. However this condition cannot always be met in practice. For example, when matching points on a curved weld joint, the seam line and the epipolar line can be tangential; this will result in multiple seam line points intersecting with epipolar line. Another example is when the epipolar line and the seam line intersect in more than one location. Therefore additional matching criterions are needed.

The performance of cross correlation is heavily affected by images with textureless regions where all the pixels are similar in intensity and also by different contrast and lighting conditions in the left and right views. Typically, images containing weld joints are featureless, repetitive and mostly textureless due to monotone steel surfaces which are mostly grey in colour. The reflections off the steel surfaces together with ambient lighting conditions greatly affect the contrast and pixel intensity between the left and right views. Therefore cross correlation can be unreliable in welding environments [62]. Even if the weld seam line pixel coordinates are extracted in both stereo images, one to one matching based on seam line pixel order is not possible, i.e. seam point 1 in image 1 to seam point 1 in image 2. Due to the relative position of the camera and perspective the seam line will have different lengths in the two images. As before with cross correlation, even with the
seam line co-ordinates in both images known, intensity based or feature matching will not work.

In online weld joint detection and tracking, sometimes only the weld start position is required. If the starting point is assumed to be on the edge of the work piece [53, 55] then the stereo matching problem is simplified. The matching pixels are identified using a corner detection method and the 3D co-ordinates are obtained from triangulation. For flat butt welds the depth can be assumed to be constant and known. Therefore only the X and Y co-ordinates need to be calculated [51, 54, 67]. If the height is known, then the calculation of X and Y offsets can be found using Equation 2.1. The assumption of a fixed height is only applicable to work pieces that sit directly on level surface. However in practice this may not always be achievable. In practice, planar butt welds may be on an incline due its position in the overall assembly or the work surface may not be level.

A laser/camera system may also be used for weld joint localisation. The results show that they have a 3D Cartesian accuracy to be within ± 0.5mm [8, 69, 71]. For a laser/camera system attached to the end-effector of a robot, the weld joint is detected by moving the robot so that the laser stripe intersects the weld joint in one particular spot. For this reason, they are typically used from a local search perspective while online to identify the start of the weld and then provide online tracking. They also rely on accurate detection of the laser stripe by the vision sensor which can be difficult when welding reflective surfaces such as aluminium or stainless steel. In a laser/camera system, the weld joint is identified by the change in shape of the laser stripe; therefore they require a gap in the joint, particularly for butt welds. By comparison, vision only systems are capable of analysing a global image of the work piece to identify and locate the entire weld joint as well as obstacles such as jigs. Furthermore vision only systems are not limited by the need for a joint gap. Therefore laser/cameras can be utilised for some online seam identification/tracking applications, they are not as versatile as vision only systems for obtaining the overall location of the weld joint and surrounding obstacles for offline path planning.
2. Literature Review

2.5 Summary

2.5.1 Research Gap in Robot and Hand-Eye Calibration

For arc welding applications, the vision system should be capable of achieving sub-millimetre accuracy. Based on the literature, the robot can be accurately calibrated using precision external measuring devices. However, the cost of such devices is prohibitive for most small sized manufacturing companies. It has been shown that the accuracy of the vision system is dependent on the accuracy of the robot, camera, robot-world and hand-eye calibration. By combining the robot kinematic model, camera, robot-world and hand-eye calibration parameters into a single objective function known as “simultaneous calibration” the propagation errors that arise from multistage calibration can be minimised. To the best of the author’s knowledge there is no simultaneous calibration of the robot kinematics, robot-world and hand-eye transformation. Existing methods assume that the robot has been pre-calibrated prior to optimisation of the hand-eye transformation.

This thesis will introduce a method that can be used to calibrate the robot arm and the robot mounted cameras simultaneously without the use of additional sensors such as external 3D measurement devices and laser scanners which add increased expense. The calibration is achieved using only the robot mounted cameras, mechanical pointer and calibration board. The robot kinematics, robot-world and hand-eye transformations are combined into a single objective function. Non-linear optimisation is used to minimise the absolute positioning errors between the robot and the world reference frame. The calibration of the internal camera parameters is “automated” to automatically identify the calibration target feature points. This improves both the calibration time and accuracy compared to a manual “point and click” method [14].
2. Literature Review

2.5.2 Research Gap in Weld Joint Detection

There are many papers published on the detection of butt welds for GTAW, however there is very little published work for vision based detection of weld joints for GMAW, and in particular the more common fillet weld. There are certainly no widely accepted and mature methods for fillet weld joint detection. While this remains unsolved, fully autonomous robotic arc welding cannot be achieved and will never be accepted in industry as a viable solution.

Figure 2.24 demonstrates a comparison between the work piece and weld joint setup in two published papers and the setup which is solved in this thesis. It can be seen that the existing method for planar butt weld detection has high contrast between background and foreground with an easily distinguishable weld joint. The fillet joint detection uses a ROI.

Figure 2.24: An example of the existing methods in [53] [63] and an example of the proposed method
2. Literature Review

In this thesis, two weld joint detection algorithms will be developed. The first method is intended only for planar butt-welds, while the second is capable of detecting butt and fillet weld joints for any shape work piece and base material such as mild steel and aluminium.

The proposed planar butt-weld joint detection algorithm is capable of automatically detecting narrow weld joints where the edges of the work piece are pressed against each other in realistic welding environments. The algorithm is capable of subtracting the background from the image without the use of a pre-defined ROI, leading to the reliable detection of weld seams for ferrous materials such as mild steel. The proposed algorithm uses the Hough Transform to detect the outside boundary of the work piece so that the background can be segmented. Once the background is segmented a set of algorithms are used to identify the weld joint.

To the best of the author’s knowledge there are no published papers that describe an algorithm for the unified automatic detection of welding joints in both the fillet and butt weld configurations for mild steel and aluminium. In this thesis, a new weld joint detection method is introduced that is capable of adaptively detecting both butt welds and fillet welds of any shape without prior knowledge of the shape or position of the joint. The proposed method analyses the entire image from a global perspective. Seeds are placed on edges that are likely to be the weld joint. Each seed is then locally assessed for its likelihood to be on the welding joint. Once the correct seed is chosen an adaptive line growing algorithm is developed to spread out and follow the weld joint until the ends of the joint are reached. The line growing method is based the assumption that the weld seam is darker than the surface of the work pieces either side of the joint.

Experimental results in a realistic workshop environment show that this method can be used to detect the welding joint for mild steel butt welds and fillet weld joints on a variety of shapes. The robustness of the detection algorithm is shown by its ability to detect the welding joint in the presence of rust, paint and mill scale on the work piece surface.
2. Literature Review

2.5.3 Research Gap in Weld Joint Localisation

Current stereo vision systems used for weld joint detection can be used to capture images for feature detection and provide absolute 3D weld seam co-ordinates for the robot. However most of the work has been done using single planar welds. Often welds are in more than one plane and are not always on flat surfaces. To achieve the kind of flexibility required in manufacturing, the stereo system should be capable of extracting the weld seams from curved and uneven surfaces.

This thesis presents two methods for robust weld joint localisation. For planar butt welds, the 2D homography transformation is utilised while for 3D fillet welds, a weld seam line and epipolar line intersection method is adopted with additional constraints to make it useful for a wider range of practical scenarios.

For planar butt welds, the geometry of the work piece itself can provide a set of corresponding feature points without the need for any additional image matching. Features such as corners of the parts can be extracted from the images and matched together based on their rough location in the image. In this thesis, the homography matrix is calculated using the point correspondences of the outside corners of the work piece. The outside corners are provided during the background segmentation of the weld joint identification process.

For the more challenging non planar fillet and butt welds, planar homography may not be practical as the weld joint lies on multiple planes. Cross correlation is another alternative; however it may not always be reliable as stated earlier. This thesis introduces a robust epipolar line and weld seam intersection method. The problem of multiple intersections is addressed using known information about the workspace and camera position to estimate the correct match based on the weld joint real world co-ordinates. The results show that this method is capable of matching the correct weld seam points for realistic work piece shapes and surface geometries.
Chapter 3 Methodology

This chapter focuses on the introduction of an automated calibration method for the robot, eye-in-hand stereo vision system as well as methods for weld joint detection and localisation. The main focus of this thesis is the development of new weld joint detection and localisation methods which can be used for path planning. Robot path planning, welding torch orientation, welding procedures and welding arc characteristics are not considered. The rest of this chapter is organised as follows: the proposed simultaneous calibration of the eye-in-hand stereo vision system and arc welding robot is given first, followed by the weld joint detection and localisation method for planar butt welds. The Chapter finishes with the combined method developed for the detection and localisation of both planar and non-planar welds joints.

3.1 Simultaneous Calibration of an Eye-in-Hand Stereo Vision System and Arc Welding Robot

3.1.1 Introduction

In this thesis, the weld joint detection and localisation are realised by a so-called eye-in-hand stereo vision system where the cameras are mounted on the robot end-effector (hand). The stereo vision system consists of two cameras rigidly mounted to the welding torch. An eye-in-hand stereo vision system offers many benefits as the cameras can be manoeuvred using the robot to get an unobstructed view of the weld joint. Their compact size also allows for better access to a wider range of welding positions. In this thesis, the stereo vision system is achieved using two cameras. Although stereo vision can be achieved using a single moving camera, dual cameras allow for efficient image capture of the weld joint as the robot does not have to be moved multiple times. The flexibility of this camera system not only allows for welding joint detection, but the calculation of the weld joint position in the robots work space which can be sent to the robot controller for automated path planning.
3. Methodology

To achieve the calculation of the real world position of the weld joint from images, the stereo vision system and robot must be calibrated. The calibration is required to establish the relationships between the cameras, the robot and the object that is being located and/or tracked using the vision system. The first step is to capture a set of images of the calibration object with known dimensions to provide correspondences between pixels and real world co-ordinates. The process of camera calibration can involve processing multiple images per camera and is arguably the most important step in the overall calibration of a vision system. It is also one of the most repetitive and time consuming stages. From this perspective, it makes sense to automate the camera calibration process.

To process these images an automatic camera calibration algorithm is developed in this thesis. The automatic calibration algorithm is used to determine the intrinsic and extrinsic parameters of the cameras. Based on the data obtained from the initial camera calibration, an estimate of the Hand-Eye and Robot-World transformation are determined. Finally the actual Hand-Eye and Robot-World transformations as well as the calibration of the robot are solved simultaneously using a non-linear optimisation method.

The calibration of the stereo vision system and the industrial robot is achieved using only the eye-in-hand camera system, a mechanical pointer and a calibration board, whereas existing methods require additional expensive 3D co-ordinate measurement devices or laser scanners to achieve the same accuracy. The results in Chapter 4 confirm that this method is capable of achieving the sub millimetre accuracy required for GMAW.

3.1.2 Co-ordinate Convention System

All co-ordinate frames shown in Figure 3.1 are established using the right-hand rule convention. Each co-ordinate frame is shown with only the direction of the $Z$ axis labelled for clarity. The world co-ordinate frame denoted by $Z_w$ is attached to the calibration object. The world frame origin and direction is established during the camera calibration. The camera co-ordinate frames for the left and right cameras are
3. Methodology

denoted by $Z_{CL}$ and $Z_{CR}$ respectively. The robot wrist flange (hand) is denoted by $Z_F$ and the robot base co-ordinate frame is denoted by $Z_R$.

The purpose of the calibration is to determine the unknown geometrical transformations between each of the co-ordinate frames shown in Figure 3.1. Once the transformations are known, then it is possible to calculate the real world position of a pixel in the image plane in the robot base frame. Therefore, if the weld joints have been identified in the image, it is possible to calculate their 3D position relative to the robots base frame, where they can be used for robot path planning.

The transformations between co-ordinate frames are represented by $4 \times 4$ homogenous matrices which contain information of the rotation and translation between the co-ordinate frames. $^{CL}T_W$ and $^{CR}T_W$ are the transformations from the world co-ordinate frame to the left and right camera frames respectively. $^{F}T_{CL}$ is the transformation matrix from the left camera to the wrist flange and is otherwise known as the hand-eye transformation. $^{CR}T_{CL}$ is the transformation matrix from the left camera frame to the right camera frame which can be calculated during the stereo calibration. $^{R}T_F$ is the transformation from the wrist flange to the robot base co-ordinate frame which can be determined using DH parameters. $^{R}T_W$ is the world co-ordinate frame to robot base co-ordinate frame transformation and is otherwise known as the robot-world transformation.
3. Methodology

3.1.3 Stereo Calibration

The rigid transformation between the left and right cameras $^{CR}T_{CL}$ can be calculated using a well-established method [14]. The transformation matrix is based on the intrinsic and extrinsic camera parameters calculated from the camera calibration. The homogenous matrix that represents the transformation from the left camera frame to the right camera frame is given by

$$
^{CR}T_{CL} = \begin{bmatrix}
^{CR}R_{CL} & ^{CR}P_{CL} \\
0 & 1
\end{bmatrix}
$$

(3.1)

where $^{CR}R_{CL}$ is the 3×3 orthogonal rotation matrix describing the relationship of the orientation of the left camera frame $CL$ to the right camera frame $CR$, and $^{CR}P_{CL}$ is 3×1 vector representing the location of the origin of the left camera frame expressed in the right camera frame.

Figure 3.1: Co-ordinate transformations
3. Methodology

3.1.4 Initialisation of the Robot-World Transformation

In this thesis, the world frame is attached to the calibration board and is shown in Figure 3.2. The final robot-world transformation will be refined using non-linear optimisation. However an initial estimate of the robot-world transformation must first be established. The initial estimate of the robot-world transformation is achieved by using the robot, which is equipped with a precision pointer (Figure 3.3), to touch and record three positions \( (P_1, P_2, P_3) \) on the calibration pattern as shown in Figure 3.2. The measurements are taken directly off the robot controller.

![Figure 3.2: World frame set up](image)

![Figure 3.3: Precision pointer attached to the end of the weld torch](image)
3. Methodology

The first point \( P_1 \) \((P_{1x}, P_{1y}, P_{1z})\) is assumed to be the origin of the world co-ordinate frame. The second point \( P_2 \) \((P_{2x}, P_{2y}, P_{2z})\) is in the direction of the world frame \( x \)-axis, while the third point \( P_3 \) \((P_{3x}, P_{3y}, P_{3z})\) is chosen so that \( \overrightarrow{P_1 P_2} \) and \( \overrightarrow{P_1 P_3} \) are on the same plane as the calibration pattern. All three points are measured in the robot frame \( R \).

From these three points, it is possible to define the unit vectors \([\hat{x}, \hat{y}, \hat{z}]\) of the \( X, Y \) and \( Z \) axes of the world frame (expressed in the robot frame \( R \)) as follows

\[
\hat{x} = (P_{2x} - P_{1x}) \hat{i} + (P_{2y} - P_{1y}) \hat{j} + (P_{2z} - P_{1z}) \hat{k}
\]

(3.2)

\[
\therefore \hat{x} = \frac{\hat{x}}{||\hat{x}||}
\]

(3.3)

where \( \hat{i}, \hat{j} \) and \( \hat{k} \) are unit vectors which describe the direction of the \( \hat{x} \) axis expressed in the robot base frame \( R \). Due to possible distortions in the printed grid pattern caused by poor adhesion, printer resolution etc. \( \overrightarrow{P_1 P_2} \) and \( \overrightarrow{P_1 P_3} \) may not be perpendicular to each other. However, the axis defined by \( \overrightarrow{P_1 P_3} \) lies on the same plane as \( \overrightarrow{P_1 P_2} \). Therefore, an estimate of the \( y \)-axis (\( \hat{y}' \)) can be obtained as:

\[
\hat{y}' = (P_{3x} - P_{1x}) \hat{i} + (P_{3y} - P_{1y}) \hat{j} + (P_{3z} - P_{1z}) \hat{k}
\]

(3.4)

\[
\therefore \hat{y}' = \frac{\hat{y}'}{||\hat{y}'||}
\]

(3.5)

where \( \hat{y}' \) is the estimate of the world frame \( y \)-axis and \( \hat{i}, \hat{j} \) and \( \hat{k} \) are unit vectors which describe the direction of the \( \hat{y}' \) axis expressed in the robot base frame \( R \). By using both \( \hat{x} \) and \( \hat{y}' \), the unit vector of the \( Z \)-axis, which is perpendicular to the plane defined by \( \overrightarrow{P_1 P_2} \) and \( \overrightarrow{P_1 P_3} \), can be calculated by the cross product of \( \hat{x} \) and \( \hat{y}' \), that is:

\[
\hat{z} = \hat{x} \times \hat{y}'
\]

(3.6)
3. Methodology

The actual unit vector of the y-axis can then be calculated as:

\[ \hat{y} = \hat{z} \times \hat{x} \]  \hspace{1cm} (3.7)

As all three points are measured from the robot coordinate frame \( R \), the three unit vectors from Equations 3.3, 3.6 and 3.7 are therefore defining the rotation component of the robot-world transformation \( ^R T_W \) with the translation component given by the three measurements of \( P_1 \).

\[
^R T_W = \begin{bmatrix}
\hat{x}_i & \hat{y}_i & \hat{z}_i & P_{ix} \\
\hat{x}_j & \hat{y}_j & \hat{z}_j & P_{iy} \\
\hat{x}_k & \hat{y}_k & \hat{z}_k & P_{iz} \\
0 & 0 & 0 & 1
\end{bmatrix} = \begin{bmatrix}
^R \hat{R}_W \\
^R \hat{P}_W
\end{bmatrix} \hspace{1cm} (3.8)
\]

where \( ^R \hat{R}_W \) is the 3×3 orthogonal rotation matrix describing the relationship of the orientation of the world frame \( W \) in the robot base frame \( R \), and \( ^R \hat{P}_W \) is 3×1 vector representing the location of the origin of the world frame expressed in the robot base frame.

Due to possible manufacturing tolerances in the robot manipulator the initial calculation given in Equation 3.8 cannot be used as a ground truth, rather as a starting point in the optimisation routine.

3.1.5 Initialisation of the Hand-Eye Transformation

In order to determine the 3D co-ordinate of a point in the world frame using triangulation, the relationship between the two camera frames and the world frame must be determined. The transformation from the world frame to the left camera frame \( ^{CL} T_W \) can then be calculated by

\[
^{CL} T_W = \left( ^R \mathcal{T}_{CL} \right)^{-1} \left( ^R \mathcal{T}_F \right)^{-1} ^R T_W \hspace{1cm} (3.9)
\]
3. Methodology

Since the transformation between the left and right camera frames \((^C^R T_{CL})\) is known, it is possible to calculate the transformation from the world frame to the right camera frame \((^C^R T_W)\) by

\[
^C^R T_W = ^C^R T_{CL}^C^R T_W
\]  

(3.10)

It can be seen in Equation 3.9 that the hand-eye transformation for the left camera frame \((^F T_{CL})\) is required to transfer a point in the image plane to the robot base coordinate frame. The initial value for the hand-eye transformation for the left camera can be calculated by re-arranging Equation 3.9

\[
^F T_{CL} = \{^F R_f \}^{-1} ^F T_W \{^F T_W \}^{-1}
\]  

(3.11)

The hand-eye calibration process can then be achieved by moving the robot through \(n\) positions and capturing images of the calibration object at these robot positions. At each position \(^F T_{CL}\) is estimated using Equation 3.11. For each calculation of \(^F T_{CL}\) the rotation component is converted to its Euler Angle equivalent. The mean of the \(n\) sets of Euler Angles, yaw \((\varphi)\), pitch \((\beta)\) and roll \((\gamma)\) are then calculated. The mean value is then used to convert back to a 3×3 orthogonal rotation matrix which becomes the true rotation component of \(^F T_{CL}\). Similarly, the mean of the translational components is calculated, and then used as the translation component of \(^F T_{CL}\).

\[
^F \hat{T}_{CL} = \begin{bmatrix}
^F \hat{R}_{CL} & ^F \hat{P}_{CL} \\
0 & 1
\end{bmatrix}
\]  

(3.12)

\[
^F \hat{R}_{CL} = \begin{bmatrix}
C\gamma C\beta & C\gamma S\beta S\varphi - S\gamma C\varphi & C\gamma S\beta C\varphi + S\gamma S\varphi \\
S\gamma C\beta & S\gamma S\beta S\varphi + C\gamma C\varphi & S\gamma S\beta C\varphi - C\gamma S\varphi \\
- S\beta & C\beta S\varphi & C\beta C\varphi
\end{bmatrix}
\]  

(3.13)

where \(^F \hat{T}_{CL}\) is the estimate of the hand-eye transformation comprising of \(^F \hat{R}_{CL}\) and \(^F \hat{P}_{CL}\) which are the average rotation and translation components respectively. \(S\) and
3. Methodology

$C$ are the sine and cosine respectively of the three Euler angles where $\varphi$ is the mean value of rotation of the camera x-axis about the robot wrist flange x-axis (yaw), $\bar{\beta}$ is the mean value of rotation of the camera y-axis about the robot wrist flange y-axis (pitch) and $\bar{\gamma}$ is the mean value of rotation of the camera z-axis about the robot wrist flange z-axis (roll). The Euler angles are depicted in Figure 3.4.

![Figure 3.4: Graphical representation of the Euler angles in Equation 3.15](image)

3.1.6 Optimised Simultaneous Calibration of the Robot, Hand-Eye and Robot-World Transformations

The calculated values from Equations 3.8 and 3.12 are based on measurements from the two cameras as well as the nominal values for the robot kinematic model. Due to manufacturing tolerances the actual link and joint measurements for the robot may vary from the nominal values given by the robot manufacturer. These differences will lead to positional errors as they accumulate through the triangulation process.

The optimisation algorithm is used in this thesis to determine the actual robot link and joint parameters and simultaneously adjust the Robot-World and Hand-Eye transformations to account for these tolerances. This effectively achieves the calibration of the robot kinematic model and the eye-in-hand stereo camera system.
3. Methodology

simultaneously. Given the nominal robot kinematic model, the actual robot kinematics will be given by

\[ ^{\text{R}}T_{\text{f,actual}} = ^{\text{R}}T_{\text{f}}(\theta_{\text{link},i}, a_{\text{link},i} + \Delta a_{\text{link},i}, d_{\text{link},i} + \Delta d_{\text{link},i}, \alpha_{\text{link},i} + \Delta \alpha_{\text{link},i}) \quad (3.14) \]

where \( \theta_{\text{link},i} \) is the joint angle of the \( i \text{th} \) link of the robot, \( a_{\text{link},i}, d_{\text{link},i} \) and \( \alpha_{\text{link},i} \) are the DH parameters for the \( i \text{th} \) link of the robot manipulator as described in Section 2.2.2 and \( \Delta a, \Delta d \) and \( \Delta \alpha \) represents the manufacturing tolerance of each of the robot link DH parameters. The actual robot-world and hand-eye transformations are then given by

\[ ^{\text{F}}T_{\text{CL,actual}} = \begin{bmatrix} ^{\text{F}}R_{\text{CL,actual}} & ^{\text{F}}P_{\text{CL,actual}} \\ 0 & 1 \end{bmatrix} \quad (3.15) \]

\[ ^{\text{R}}T_{\text{W,actual}} = \begin{bmatrix} ^{\text{R}}R_{\text{W,actual}} & ^{\text{R}}P_{\text{W,actual}} \\ 0 & 1 \end{bmatrix} \quad (3.16) \]

where

\[ ^{\text{F}}R_{\text{CL,actual}} = \begin{bmatrix} ^{\text{F}}R_{\text{CL,11}} & ^{\text{F}}R_{\text{CL,12}} & ^{\text{F}}R_{\text{CL,13}} \\ ^{\text{F}}R_{\text{CL,21}} & ^{\text{F}}R_{\text{CL,22}} & ^{\text{F}}R_{\text{CL,23}} \\ ^{\text{F}}R_{\text{CL,31}} & ^{\text{F}}R_{\text{CL,32}} & ^{\text{F}}R_{\text{CL,33}} \end{bmatrix} \quad (3.17) \]

\[ ^{\text{F}}R_{\text{CL,11}} = C(\hat{\gamma}_{CL} + \Delta^F \gamma_{CL})C(\hat{\beta}_{CL} + \Delta^F \beta_{CL}) \quad (3.18) \]

\[ ^{\text{F}}R_{\text{CL,12}} = C(\hat{\gamma}_{CL} + \Delta^F \gamma_{CL})S(\hat{\beta}_{CL} + \Delta^F \beta_{CL})S(\hat{\phi}_{CL} + \Delta^F \varphi_{CL}) - S(\hat{\gamma}_{CL} + \Delta^F \gamma_{CL})C(\hat{\phi}_{CL} + \Delta^F \varphi_{CL}) \quad (3.19) \]

\[ ^{\text{F}}R_{\text{CL,13}} = C(\hat{\gamma}_{CL} + \Delta^F \gamma_{CL})S(\hat{\beta}_{CL} + \Delta^F \beta_{CL})C(\hat{\phi}_{CL} + \Delta^F \varphi_{CL}) + S(\hat{\gamma}_{CL} + \Delta^F \gamma_{CL})S(\hat{\phi}_{CL} + \Delta^F \varphi_{CL}) \quad (3.20) \]
3. Methodology

\[ F_{R_{CL,21}} = S(F \dot{\gamma}_{CL} + \Delta^F \gamma_{CL})C(F \dot{\beta}_{CL} + \Delta^F \beta_{CL}) \]  
(3.21)

\[ F_{R_{CL,12}} = S(F \dot{\gamma}_{CL} + \Delta^F \gamma_{CL})S(F \dot{\beta}_{CL} + \Delta^F \beta_{CL})C(F \dot{\phi}_{CL} + \Delta^F \phi_{CL}) + C(F \dot{\gamma}_{CL} + \Delta^F \gamma_{CL})C(F \dot{\phi}_{CL} + \Delta^F \phi_{CL}) \]  
(3.22)

\[ F_{R_{CL,23}} = S(F \dot{\gamma}_{CL} + \Delta^F \gamma_{CL})S(F \dot{\beta}_{CL} + \Delta^F \beta_{CL})C(F \dot{\phi}_{CL} + \Delta^F \phi_{CL}) - C(F \dot{\gamma}_{CL} + \Delta^F \gamma_{CL})S(F \dot{\phi}_{CL} + \Delta^F \phi_{CL}) \]  
(3.23)

\[ F_{R_{CL,31}} = -S(F \dot{\beta}_{CL} + \Delta^F \beta_{CL}) \]  
(3.24)

\[ F_{R_{CL,32}} = C(F \dot{\beta}_{CL} + \Delta^F \beta_{CL})S(F \dot{\phi}_{CL} + \Delta^F \phi_{CL}) \]  
(3.25)

\[ F_{R_{CL,33}} = C(F \dot{\beta}_{CL} + \Delta^F \beta_{CL})C(F \dot{\phi}_{CL} + \Delta^F \phi_{CL}) \]  
(3.26)

\[ F_{P_{CL,actual}} = \begin{bmatrix} F\dot{X}_{CL} + \Delta^F X_{CL} \\ F\dot{Y}_{CL} + \Delta^F Y_{CL} \\ F\dot{Z}_{CL} + \Delta^F Z_{CL} \end{bmatrix} \]  
(3.27)

where \( F\dot{\phi}_{CL}, F\dot{\beta}_{CL} \) and \( F\dot{\gamma}_{CL} \) are the three Euler angles which represent the rotation component of the initial estimate of the left camera to robot wrist flange transformation \((F T_{CL,actual})\), \(S\) and \(C\) are the sine and cosine of the Euler angles. \(F\dot{X}_{CL}, F\dot{Y}_{CL}\) and \(F\dot{Z}_{CL}\) are the translation component the initial estimate of \(F T_{CL,actual}\) and \(\Delta^F \phi_{CL}, \Delta^F \beta_{CL}, \Delta^F \gamma_{CL}, \Delta^F X_{CL}, \Delta^F Y_{CL}\) and \(\Delta^F Z_{CL}\) represents the unknown geometrical variation in the rotation and translation components of the hand-eye transformation introduced by the manufacturing tolerances of the robot. The actual world frame to robot base frame transformation is calculated in the similar manner which is given by

\[ R_{W,actual} = \begin{bmatrix} R_{W_{11}} & R_{W_{12}} & R_{W_{13}} \\ R_{W_{21}} & R_{W_{22}} & R_{W_{23}} \\ R_{W_{31}} & R_{W_{32}} & R_{W_{33}} \end{bmatrix} \]  
(3.28)
3. Methodology

where

\[ ^R R_{w_{11}} = C^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} C^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} \]  \hspace{1cm} (3.29)

\[ ^R R_{w_{12}} = C^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} S^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} S^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} - S^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} C^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} \]  \hspace{1cm} (3.30)

\[ ^R R_{w_{13}} = C^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} S^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} C^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} + S^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} S^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} \]  \hspace{1cm} (3.31)

\[ ^R R_{w_{21}} = S^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} C^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} \]  \hspace{1cm} (3.32)

\[ ^R R_{w_{12}} = S^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} S^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} S^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} + C^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} C^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} \]  \hspace{1cm} (3.33)

\[ ^R R_{w_{23}} = S^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} S^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} C^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} - C^{( ^R \hat{\gamma}_w + \Delta ^R \gamma_w )} S^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} \]  \hspace{1cm} (3.34)

\[ ^R R_{w_{31}} = -S^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} \]  \hspace{1cm} (3.35)

\[ ^R R_{w_{32}} = C^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} S^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} \]  \hspace{1cm} (3.36)

\[ ^R R_{w_{33}} = C^{( ^R \hat{\beta}_w + \Delta ^R \beta_w )} C^{( ^R \hat{\phi}_w + \Delta ^R \phi_w )} \]  \hspace{1cm} (3.37)

\[ ^R P_{w_{\text{actual}}} = \begin{bmatrix} ^R \hat{X}_w + \Delta ^R X_w \\ ^R \hat{Y}_w + \Delta ^R Y_w \\ ^R \hat{Z}_w + \Delta ^R Z_w \end{bmatrix} \]  \hspace{1cm} (3.38)

where \(^R \hat{\phi}_w\), \(^R \hat{\beta}_w\) and \(^R \hat{\gamma}_w\) are the three Euler angles which represent the rotation component of the initial estimate of the robot-world transformation \( ^R \hat{T}_{w_{\text{actual}}} \). \( S \) and \( C \) are the sine and cosine of the Euler angles. \(^R \hat{X}_w\), \(^R \hat{Y}_w\) and \(^R \hat{Z}_w\) are the translation component the initial estimate of the robot-world transformation and \( \Delta ^R \phi_w, \Delta ^R \beta_w, \Delta ^R \gamma_w \).
3. Methodology

\( \Delta^r y_w, \Delta^r x_w, \Delta^r y_w \) and \( \Delta^r z_w \) represents the unknown geometrical variation in the rotation and translation components of the robot-world transformation introduced by the manufacturing tolerances in the robot.

The unknown manufacturing tolerances for the robot links and the geometrical variations in the hand-eye and robot-world transformations introduced by the robot manufacturing tolerances can be found by minimising the following non-linear objective function

\[
\min \sum_{i=1}^{n} (\mathcal{C}L T_{iW, \text{calculated}} - \mathcal{C}L T_{iW, \text{measured}})^2
\]

(3.39)

where \( n \) is the number of calibration configurations and \( \mathcal{C}L T_{iW, \text{calculated}} \) is given by

\[
\mathcal{C}L T_{iW, \text{calculated}} = (r_{T_{CL, \text{actual}}})^{-1} (r_{T_{F, \text{actual}}})^{-1} r_{T_{W, \text{actual}}}
\]

(3.40)

The value for \( \mathcal{C}L T_{W, \text{measured}} \) for each robot calibration position can be obtained from the camera calibration. The optimisation is constrained so that the rotation unit vectors of \( r_{T_{F, \text{actual}}}, \mathcal{C}L T_{F, \text{actual}} \) and \( r_{T_{W, \text{actual}}} \) remain in orthonormal by introducing the following constraints during minimisation

\[
\sqrt{r_{11}^2 + r_{12}^2 + r_{13}^2} = 1
\]

(3.41)

\[
\sqrt{r_{21}^2 + r_{22}^2 + r_{23}^2} = 1
\]

(3.42)

\[
\sqrt{r_{31}^2 + r_{32}^2 + r_{33}^2} = 1
\]

(3.43)

\[
\sqrt{r_{11}^2 + r_{21}^2 + r_{31}^2} = 1
\]

(3.44)

\[
\sqrt{r_{12}^2 + r_{22}^2 + r_{32}^2} = 1
\]

(3.45)

62
3. Methodology

\[
\sqrt{r_{13}^2 + r_{23}^2 + r_{33}^2} = 1 \tag{3.46}
\]

\[
r_{11}r_{21} + r_{12}r_{22} + r_{13}r_{23} = 0 \tag{3.47}
\]

\[
r_{21}r_{31} + r_{22}r_{32} + r_{23}r_{33} = 0 \tag{3.48}
\]

\[
r_{11}r_{31} + r_{12}r_{32} + r_{13}r_{33} = 0 \tag{3.49}
\]

where \( r_{nm} \) represents the element on the \( n^{th} \) row and \( m^{th} \) column of the particular transformation matrix \( \left( R_{T_{F_{actual}}, CL}, R_{T_{W_{actual}}} \right) \).

3.1.7 The Proposed Automated Camera Calibration Method

Camera calibration is achieved by capturing multiple images of a calibration pattern. The calibration pattern provides a set of feature points with known 3D real world co-ordinates. By obtaining the correspondences between the feature points in the 2D image plane and the 3D real world from multiple images, the camera parameters can be determined. Because camera calibration for a stereo system can involve processing multiple images per camera is time consuming and highly repetitive. From this perspective, it makes sense to automate the camera calibration process.

In this thesis the calibration method in [14] will be used to calculate the intrinsic camera parameters. A grid detection algorithm is developed in this thesis to automatically detect the grid corners of a checkerboard calibration pattern. The flowchart in Figure 3.5 is an overview of the proposed automated camera calibration method. The grid area is selected based on the boundaries defined by coloured markers. The origin point of the World Frame is identified by using red makers.
3. Methodology

**Figure 3.5: Automated camera calibration flowchart**

The proposed grid pattern layout is shown in Figure 3.6. The red markers comprising of a red square and a red dot indicate the origin of the World frame. The blue markers comprising of blue squares and blue dots indicate the remaining boundary points that define the calibration area. Defining the calibration area with coloured squares allows for image segmentation and removes interference from background objects. It is important to differentiate the origin from the other points, as this origin will be used as a reference point in the calculation of the geometrical relationship between the stereo cameras. The red markers also allow for the origin point to be recognised regardless of the image orientation. The dots are used to determine which corners of the squares are used to define the boundary of calibration area.

**Figure 3.6: Proposed Calibration grid with 30mm × 30mm squares and 5mm diameter dots**
3. Methodology

3.1.7.1 Origin Point Recognition

From the colour image of the calibration board (Figure 3.6) the red square and red dot are segmented by a red filter using the method in [89] so that only the red pixels of the image remain while the rest of the image is converted to grayscale as shown in Figure 3.8. This is achieved using Equation 3.50.

![Figure 3.7: RGB colour image of calibration board](image)

\[ I_{RB}(u,v) = \begin{cases} I_{RGB}(u,v), & C1 \land C2 = \text{TRUE} \\ I_{GRAY}(u,v), & \text{otherwise} \end{cases} \tag{3.50} \]

where

\[ C1 : I_{RGB}(R)(u,v) > \max(I_{RGB}) \times 0.1 \]
\[ C2 : I_{RGB}(R)(u,v) = \max[I_{RGB}(R)(u,v), I_{RGB}(G)(u,v), I_{RGB}(B)(u,v)] \]

where, \( I_{RB}(u,v) \) is the output from the red filter of the pixel at coordinate location of \( u \) and \( v \), \( I_{RGB} \) is the original \( RGB \) colour image, \( I_{RGB}(R), I_{RGB}(G) \) and \( I_{RGB}(B) \) are the red, green and blue components of the RGB image respectively. Due to the image digitisation process, it is possible for the composition of the RGB values for individual pixels in the black squares to contain a higher blue intensity level. A scaling factor of 0.1 is used to suppress the blue pixels in the black squares. This value was chosen for this particular calibration board and CCD cameras through experimentation. The “\( \land \)” is the logic ‘AND’ operation, “\( \text{TRUE} \)” is the logical
3. Methodology

‘TRUE’, ‘==’ is the logical equal, i.e., C2 is only true when both sides of C2 is equal. $I_{GRAY}$ is the gray level image converted from the colour image using the well-known equation.

$$I_{GRAY}(u,v) = \begin{bmatrix} 0.3 & 0.59 & 0.11 \end{bmatrix} \begin{bmatrix} I_{RGB} \{ R \}(u,v) \\ I_{RGB} \{ G \}(u,v) \\ I_{RGB} \{ B \}(u,v) \end{bmatrix}$$

(3.51)

Figure 3.8: RGB image after the red filter using Equation 3.50

When Equation 3.50 is applied to the image shown in Figure 3.7, the red image (Figure 3.8) is obtained. It is then subtracted from the original RGB image using Equation 3.52 below. The resulting image leaves the red square and dot clearly visible, allowing for further segmentation. The result is shown in Figure 3.8.

$$I_R = |I_{RF} - I_{RGB}|$$

(3.52)
3. Methodology

The image \( (I_R) \) is then converted to a black and white binary image using adaptive thresholding [90]. Equation 3.53 is then used to remove all erroneous pixel clusters with an area smaller than a set threshold leaving only the red square.

\[
I_{\text{square}} = \begin{cases} 
1 & \text{Area} > T_{\text{square}} \\
0 & \text{otherwise}
\end{cases}
\]  \hspace{1cm} (3.53)

where \( T_{\text{square}} \) is the threshold used to remove any noise after the red filtering, \( \text{Area} \) is the number of connected red pixels (the white pixels in the binary image). The Harris corner detector [77] is used to find the corners of the square. The correct corner is determined by calculating the Euclidean distance from each Harris corner to the centre of the red dot. The corner with the smallest distance to the circle is then used as the origin point. The red dot is detected by converting the red filtered image to a black and white binary image and using Equation 3.54.

\[
I_{\text{circle}} = \begin{cases} 
1 & (\text{Area} > T_{\text{dot, min}}) \land (\text{Area} < T_{\text{dot, max}}) = \text{TRUE} \\
0 & \text{otherwise}
\end{cases}
\]  \hspace{1cm} (3.54)

where “TRUE” is the logical ‘TRUE’ and \( T_{\text{dot, min}} \) and \( T_{\text{dot, max}} \) are set to ignore any erroneous areas left after binary conversion. The Harris corners and the centroid of the red dot are shown in Figure 3.10. Since the dimensions of the coloured squares and dots are known from the setup, the thresholds can be estimated from the known

Figure 3.9: Image after segmentation using Equation 3.52
3. Methodology

working range of the camera. In this thesis, the maximum working range of the camera is around 400-500mm above the table. It was found that within this camera range that the pixel area of the squares is always greater than 5000 pixels and the area of the dots is within 30 to 600 pixels. Therefore it was found that \( T_{\text{square}} = 5000, T_{\text{dot}, \text{min}} = 30 \) and \( T_{\text{dot}, \text{max}} = 600 \) was sufficient for the setup in this thesis.

![Figure 3.10: Red Square and dot with Harris corners](image)

3.1.7.2 Remaining Calibration Board Boundary Points

After the red markers are identified, the remaining 3 boundary points of the calibration board can be determined by using the blue markers. To achieve this, a blue filter similar to that of the red filter is introduced.

\[
I_{BF}(u, v) = \begin{cases} 
I_{RGB}(B)(u, v), & C_3 \wedge C_4 = \text{TRUE} \\
I_{GRAY}(u, v), & \text{otherwise}
\end{cases}
\]

where

\( C_3 : I_{RGB}(B)(u, v) > \max(I_{RGB}) \times 0.1 \)
\( C_4 : I_{RGB}(B)(u, v) = \max[I_{RGB}(R)(u, v), I_{RGB}(G)(u, v), I_{RGB}(B)(u, v)] \)

where \( I_{BF} \) is the output from the blue filter (blue filtered pixel), other notions are similar to those in Equation 3.50. The blue filtered image is then subtracted from the original RGB image, leaving only the blue squares and dots in the similar manner that the red square and circle were segmented using Equations 3.53 and 3.54.
3. Methodology

\[ I_B = |I_{BF} - I_{RGB}| \] (3.56)

The Harris corner detector is then used to find the corners of the blue squares. In the same manner as the red squares, the smallest Euclidian distance from each blue square corner to the centre of its blue dot is used to determine the correct corner. The Harris corners and blue circle centroids are shown in Figure 3.11, and the final resulting corners are shown in Figure 3.12. The four boundary points are then used in the existing method [14].

![Figure 3.11: Blue squares and dots with Harris corners](image)

![Figure 3.12: Calibration board boundary corners](image)
3. Methodology

3.2 Planar Weld Joint Detection

3.2.1 Introduction

This section introduces a vision based weld joint detection algorithm that is capable of automatically detecting weld joints in a planar butt-joint configuration. An example of a typical butt weld joint is shown in Figure 3.1.

![Example of a planar butt weld joint](image)

*Figure 3.13: Example of a planar butt weld joint*

The algorithm is capable of subtracting the background from the image without the use of a pre-defined ROI, leading to the reliable detection of weld seams for ferrous materials such as mild steel. The proposed algorithm uses the Hough Transform to detect the outside boundary of the work piece so that the background can be removed. Once the background is removed a set of algorithms are used to identify the welding joints.

An overview describing the weld joint detection process is shown in Figure 3.14. 1) In the first stage pre-processing filters are used to smooth the image; 2) the second stage is a background segmentation algorithm that uses Hough lines to segment the work piece from the background so that the weld joint can be identified; 3) in the final stage, the joint is identified by analysing the remaining edges in the segmented image and removing those that do not belong to the weld joint, such as the work
3. Methodology

piece boundary and scratches. The final seam line is then ready for localisation and implementation by a robotic welding system.

The main contribution of this thesis in this area is the introduction of a method for autonomous weld joint detection for planar butt weld joints, particularly for ferrous materials such as mild steel with narrow weld joints where the edges of the work pieces are pressed against each other. It is capable of identifying the weld joint from a global perspective without the need for a ROI. It is therefore capable of identifying the weld joint without prior knowledge of the shape or location of the weld joint in the image. The proposed method is designed to be implemented in realistic welding environments and does not rely on high contrast between the work piece and background as is the case for current butt weld joint detection methods for aluminium GTAW.

![Planar butt weld joint detection overview](#)

**Figure 3.14: Planar butt weld joint detection overview**

3.2.2 Pre-processing

3.2.2.1 Image conversion and smoothing

The first stage in the segmentation of the work piece and the background is to convert the colour image $I_{RGB}$ to a grayscale image $I_{GRAY}$. This can be achieved using Equation 3.31. For images of a steel work pieces on a steel workbench, it was found that there is no advantage of using RGB over grayscale as the image contains very
3. Methodology

similar shades of grey. Therefore, grayscale is sufficient for image processing of welding images.

The second stage of the pre-processing is to prepare the image for background segmentation. Median filters are employed to smooth the image so that most of the lines and features in the background as well as scratches on the work piece are not detected when edge identification is applied. The benefit of using the median filter for smoothing is that the background lines are blurred, while the integrity of the stronger edges of the work piece are preserved.

When a median filter is applied multiple times, the noise/scratches in the image can be reduced further. In this thesis it was found that by applying the median filter twice, the resulting image is adequately smoothed for further processing. The neighbourhood size also affects the filtering results. The effect of using a median filter to smooth the background is shown in Figure 3.15. For the images used in this thesis, it was found that a neighbourhood size of 10x10 was suitable for steel Demmeler welding benches. This neighbourhood size allows for smoothing of the scratches and markings such as rust on the work bench surface without smoothing the boundary edges of the work piece. This allowed for accurate edge detection of the work piece boundary while reducing the number of edges calculated by scratches and markings on the workbench.

![Grayscale image and the image after median filtering](image)

*Figure 3.15: a) Grayscale image and b) the image after median filtering*
3. Methodology

3.2.2.2 Pre-processing Edge Identification

The last pre-processing stage is to perform edge identification on the median filtered images. The Hough Transform [91] will be used to detect the outside boundary of the work piece based on these edges. The background and work piece can then be segmented based on the Hough lines.

In this thesis, the Sobel edge identification algorithm is used for edge identification. The Sobel operator was found to provide effective edge identification for this step as it will detect the edges of the work piece without including too many additional edges such as from scratches, shadows or bright spots. The grayscale edge image produced by the Sobel edge algorithm is converted to a black and white binary image using an adaptive threshold [30]. To ensure that the edges are unbroken, the binary image is dilated and eroded so that the edge lines have a width of one pixel. The resulting edge image is shown in Figure 3.16. Single pixel edge lines allow the Houghline detection method to return more reliable line functions. This speeds up and simplifies the background subtraction process as the Hough lines will be used to determine the boundaries of the work piece.

![Figure 3.16: Pre-processing edge image](image-url)
3. Methodology

3.2.3 Background Segmentation

3.2.3.1 Hough Lines

Existing methods for segmenting the background either use a predefined ROI or a highly contrasted work piece and background. In this thesis, a method of automatically segmenting the background is introduced. This is accomplished by using Hough lines to detect possible edges of the work piece. The Hough lines are used as a path for local sliding search windows. The sliding search windows will be used to compare the grayscale pixel intensity on either side of the Hough line. By comparing the pixel intensities, it is possible to determine if the Hough line is on the edge of the work piece or on the background. Mathematically, Hough lines can be described by [91]

\[ \rho = u \cos \theta + v \sin \theta, \quad \theta \in [0, 2\pi] \]  \hspace{1cm} (3.57)

where \( \rho \) is the distance between the edge pixel point and the image origin. \( \theta \) is the angle between \( \rho \) and the \( v \) axis of the image plane as shown in Figure 3.17 and is between 0 and 2\( \pi \).

\[ (0,0) \]

\[ u \]

\[ v \]

\[ \theta \]

\[ \rho \]

Figure 3.17: Hough transform

74
3. Methodology

To determine which edge pixels form a straight line, $\rho$ and $\theta$ are grouped into bins in an array called the accumulator. Each bin contains a straight line segment. The highest values in the accumulator are the most refined straight lines in the image. To limit the number of lines returned, a threshold can be placed on the accumulator so that only the strongest lines are shown.

$$T_i = \beta H_{\text{max}}$$  \hspace{1cm} (3.58)

where $T_i$ is the threshold, $\beta$ is the threshold multiplier which represents the percentage of the maximum accumulator value $H_{\text{max}}$ that will be used. The larger the values of $\beta$, the fewer Hough lines are detected. Similarly the lower the values of $\beta$, the more Hough lines are detected. The relation between number of Hough lines and the selection of $\beta$ is determined by examining the number of edges calculated during edge detection. For example if the work piece or background has particularly heavy scratching or markings which are not removed during smoothing, then they will be show up as edges. To determine which of the edges in the image are the work piece boundary, the threshold is used to remove the weaker edges associated with scratches and keep the stronger boundary edges rated by their accumulator values. In this Thesis, the value of $\beta$ was found empirically by analysing many images of weld joints taken from the robot. The calculated Hough lines (in red) are shown in Figure 3.18 using $\beta=0.22$.  

75
3. Methodology

Figure 3.18: Edge image with Hough lines ($\beta=0.22$)

3.2.3.2 Search Windows

The Hough lines shown in Figure 3.18 are sorted into line segments according to the points at which they intersect with each other. The Hough lines with their intersections are shown in Figure 3.19. It can be seen that multiple line segments are returned including lines that pass through the background.

To determine which lines enclose the work piece, each line segment is used as a path for a set of sliding windows $f$ and $g$ to follow (Figure 3.20). The windows are used to compare the value of the grayscale pixel intensity on either side of the line according to the following equations.
3. Methodology

Figure 3.19: Hough line edge segments

Figure 3.20: Search windows
3. Methodology

\[
f_{avg_n} = \frac{\sum_{i=-w}^{w} \sum_{j=-w}^{w} I_{g} \left(u_n - \left(\frac{2w+1}{2}\right)i + 1 , v_n - \left(\frac{2w+1}{2}\right)j + 1\right)}{2(2w+1)}
\]

\[
g_{avg_n} = \frac{\sum_{i=-w}^{w} \sum_{j=-w}^{w} I_{g} \left(u_n + \left(\frac{2w+1}{2}\right)i + 1 , v_n + \left(\frac{2w+1}{2}\right)j + 1\right)}{2(2w+1)}
\]

where \(u_n\) and \(v_n\) are the co-ordinates of the \(n^{th}\) point on the line segment, \(w\) is the window which has a width \(\times\) height of \(2w+1\) pixels and \(f_{avg_n}\) and \(g_{avg_n}\) are the average pixel intensity values in the \(f_n\) and \(g_n\) windows respectively.

The averaged value of each window is then normalised as a percentage of 255, which is the highest pixel intensity value in a grayscale image and represents the colour white. This gives a base line to measure the difference between the two windows.

\[
f_{norm} = \left(\frac{f_{avg_n}}{255}\right) 100\%
\]

\[
g_{norm} = \left(\frac{g_{avg_n}}{255}\right) 100\%
\]

Finally, the average value of the normalised windows over the length of the line segment is calculated and the percentage difference between work piece and background is compared.

\[
F = \frac{\sum_{n=1}^{N} f_{norm_n}}{N}
\]

\[
G = \frac{\sum_{n=1}^{N} g_{norm_n}}{N}
\]
3. Methodology

\[ D = |F - G| \]  

(3.65)

where \( N \) is the total number of windows on each side of the line segment. The line segment is then on the edge of the work piece and the background if \( D \) is greater than the percentage difference threshold \( T_2 \).

\[ \text{Edgeline} = \begin{cases} \text{True} & D > T_2 \\ \text{False} & \text{otherwise} \end{cases} \]  

(3.66)

where \( D \) is a measure of the average percentage difference between the pixel intensity between the background and weldment. Comparing the edges as the average percentage difference allows for varying lighting conditions such as shadows and bright spots. For example, if the line is along an edge in the background then the value of \( D \) will be minimal as the average pixel intensity on either side of the line are similar. If the line is on an edge between the work piece and the background, then depending on the contrast between the two, \( D \) will either be small or large but will always be larger than that for the background lines. The threshold at which an edge line is identified correctly is set by \( T_2 \). The threshold needs to be a value that is large enough so that false lines are not detected and not too small so that the edges of interest are not ignored. It was found that in this thesis that a value of \( T_2=10\% \) was sufficient to segment the background and foreground.

Once all the lines have been searched and the boundary lines are returned, the background can be removed by setting all pixels outside the boundary to zero. The resulting image is shown in Figure 3.21.
3. Methodology

3.2.4 Weld Joint Detection

3.2.4.1 Edge Identification in Foreground Image

Once the background has been segmented, it is much easier to identify the weld joint as the search region has been significantly reduced. The Sobel edge identification algorithm is again used to calculate the edge image. The resulting edge image is shown in Figure 3.22. It can be seen in Figure 3.22 that the weld joint is clearly visible. However there are other edges such as the work piece outline and reflective patches of light have also been detected. It is not a trivial process to identify the weld joint until these lines have been removed.
3. Methodology

Figure 3.22: Edge identification in foreground image

3.2.4.2 Work Piece Boundary Removal

The outside boundary can be removed by calculating the boundary of all 8-connected pixel neighbourhoods. The Boundaries can be found by using a contour tracing algorithm such as Moore Neighbourhoods [92]. The pixels comprising the outside boundary are set to a value zero and is shown in Figure 3.23.

Figure 3.23: Work piece boundary removed
3. Methodology

3.2.4.3 Weld joint Seam Line Detection

It is obvious from the images above, that the weld seam line is the longest line left in the image. However this line may not be continuous depending on the effectiveness of the edge identification. A solution to this would be to dilate and then erode the image. The remaining small clusters of pixels caused by scratches and reflected light patches; depending on their vicinity to the seam line could be merged with the seam line leading to unusable results. Therefore these lines must first be removed. They can be removed by calculating their area and comparing it to a threshold. If the area is less than the threshold, the pixel values in the cluster can be set to zero using the Equation below

\[
I = \begin{cases} 
1 & \text{Area} > T_3 \\
0 & \text{otherwise} 
\end{cases}
\]  

(3.67)

where *Area* is the number of connected white pixels in the binary image. Once the small areas are removed, the image can be dilated and eroded leaving a continuous seam line. The resulting image is shown in Figure 3.24. It can be seen that while not all the erroneous pixels are removed, the majority have. It is now clear that the longest continuous line left in the image is the weld joint.

The seam line is then found by calculating the length of the remaining pixel clusters along the vertical and horizontal axes of the image plane. The cluster with the longest length in both of the image axes can be safely assumed to be the seam line and is shown in Figure 3.25.
3. Methodology

![Image after small area removal](image1.png)

*Figure 3.24: Image after small area removal*

![Detected weld joint](image2.png)

*Figure 3.25: Detected weld joint*

3.2.4.4 *Post-processing of the Weld joint Seam Line*

There may be some instances where the small areas of pixels may not be completely removed around the seam line (Figure 3.26) before the image is dilated. This is because the pixel cluster area is larger than the threshold in Equation 3.47 due to reflections or scratches close to the weld joint. If they are not removed then they can cause “spurs” along the seam line where they are merged during dilation. These can be removed by smoothing the seam line.
3. Methodology

To ensure that the seam line is smooth and properly follows contour of the seam, the A* algorithm [93-95] is used. The A* algorithm is a path planning technique used to find the most efficient path between a starting point and an end point. In terms of post processing the welding seam, the A* algorithm was chosen as it was developed to find the shortest path in a bitmap environment, the same environment as a computer vision image. Therefore it can be used to smooth the seam line and remove any “spurs” as shown in Figure 3.27. The cost function was set as the checkerboard distance from one pixel to another. The starting point is one end of the seam line and the goal the other. All pixels in the seam line are available as possible moves and any pixel not part of the seam line is an obstacle.

![Image](image1.png)

*Figure 3.26: Small areas not removed by threshold in Equation 3.44*

![Image](image2.png)

*Figure 3.27: a) Weld joint with spurs b) after post processing*
3. Methodology

In summary, the proposed method has made new contributions to the area of weld joint identification for narrow weld joints where the edges of the work piece are pressed against each other in ferrous materials for GMAW. The proposed algorithm does not rely on high contrast between the background and foreground, which is the case in existing methods for aluminium in GTA W. The proposed method is also capable of identifying the weld joint without a ROI as it can identify the weld joint without prior knowledge of the shape or position of the weld joint from a single image. These key contributions provide an accurate, reliable and practical method of planar butt weld joint identification which can be implemented in industrial welding environments.

3.3 Image Matching for Planar Weld Joints

3.3.1 Introduction

For planar butt welds, image matching can be achieved by utilising a 2D homography transformation. The calculation of the homography matrix requires at least 4 sets of corresponding image points. The calculation of the corresponding points is not a straightforward task in the welding environment. However, these points can be provided by the outside corners of the work piece and matched together based on their rough location in the image. The outside corners are provided during the background segmentation of the weld joint identification process as described in the previous section.

After weld joint identification using the method from Section 3.2, the steps for the proposed image matching method are shown in Figure 3.28. 1) The outside corners of the work piece are found using the Hough lines for background segmentation from Section 3.2.3; 2) The 2D homography is calculated from the stereo images using feature points calculated in step 1; 3) The matching seam line points are calculated. These methods are described in detail in the sections below.
3. Methodology

3.3.1 Corner Feature Detection

The image co-ordinates of the corners are found using the Hough lines obtained during background segmentation. The corners are calculated from the Hough lines intersections. An example of the corner points for the left and right images are shown in Figure 3.29. The advantage of using the outside corners is the ability to determine which the corresponding corners are by comparing their image co-ordinates without the need for further image processing. For example, it is straightforward to match the corners according to top left, bottom left, bottom right and top right. Furthermore, the outside corners are on the same plane as the weld seam, which increases the accuracy of the homography calculation. The workpiece corner and boundary detection in this thesis is only limited to straight line boundaries.
3. Methodology

3.3.3 Homography Calculation

The corresponding corner points are then used to calculate the 2D homography matrix $H$ using Equation 2.27 in Section 2.4.3.

3.3.4 Image Matching and Triangulation

Given the homography matrix $H$, the corresponding weld seam points between the stereo images can be calculated using Equation 2.23 which is given again below as Equation 3.68. The reference points in the left image are given by seam line points which are calculated using the weld joint detection algorithm in Section 3.2. The matching seam line point in the right image is given by

$$
\begin{bmatrix}
u_{R(i)} \\
v_{L(i)} \\
1
\end{bmatrix} = H
\begin{bmatrix}
u_{L(i)} \\
v_{R(i)} \\
1
\end{bmatrix}
$$

(3.68)

where $u_{L(i)}, v_{L(i)}$ and $u_{R(i)}, v_{R(i)}$ are corresponding image points for the $i^{th}$ seam line point from the left and the right image respectively. The corresponding points can then be used to calculate the 3D Cartesian co-ordinates of the weld joint in the robot base using the Equation below

$$
^w P = ^w T_W
\begin{bmatrix}
X_W \\
Y_W \\
Z_W \\
1
\end{bmatrix}
$$

(3.69)

where $(X_W, Y_W, Z_W)^T$ are the 3D co-ordinates of the weld joint in the world co-ordinate frame which can be calculated using Equations 2.31, 2.34 and 2.35. $^w T_W$ is the world frame to robot base frame transformation given by Equation 3.16. The 3D co-ordinates can then be sent to the robot controller for path planning.
3. Methodology

It can be seen from Equation 3.69, that the final calculation of the weld joint position in the robot base frame is dependent on the accuracy of the calibration. As the calculation of the transformation matrix $^rT_w$ is dependent on the calculation of the cameras, robot, hand-eye and robot-world transformations as given in Section 3.1.

In Chapter 4, the effectiveness of this method will be benchmarked against homography estimated by RANSAC and NCC through experimentation using realistic work pieces. It will be shown that it is difficult to autonomously obtain the required correspondences using RANSAC and that NCC can produce unreliable results.

3.4 Combined Planar and Non Planar Weld Joint Detection

3.4.1 Introduction

In this section a novel approach to the combined detection of both fillet and butt weld joints is introduced using an adaptive line growing algorithm developed in this thesis. The proposed method analyses the entire image from a global perspective. Seeds are placed on edges that are likely to be the weld joint. Each seed is then locally assessed for its likelihood to be on the welding joint. Once the correct seed is chosen an adaptive line growing algorithm is developed to spread out and follow the weld joint until the ends of the joint are reached. The line growing method is based the assumption that the weld seam is darker than the surface of the work pieces either side of the joint.

An overview of the detection algorithm is shown below in Figure 3.30. It contains 4 steps: 1) The first step is to capture stereo images. The stereo cameras and robot setup are assumed to be calibrated using the method from Section 3.1; 2) The images are then converted to binary edge images where the initial seed locations are determined by eroding each edge segment to a single pixel; 3) Each of the initial seed locations is grown outward using the line growing method developed in this thesis to
find weld joints. Based on growth properties of the initial seeds, they can be categorised as either part of the joint or not; 4) The final seed pixel is then selected from analysing the local neighbourhood of each of the remaining seeds; 5) The final line is then grown along the weld joint. The weld joint is found in both the left and right image for the weld joint localisation in Section 3.5.

Figure 3.30: Overview of the combined fillet and butt weld joint detection method

This method fills a void that currently exists in 3D weld joint detection. Currently there are no mature methods for the detection of both fillet and weld joints. The method developed in this thesis provides the first complete solution for adaptive detection of fillet and butt weld joints, regardless of base material and surface imperfections. This solves the two of the five key steps towards autonomous robotic welding as described in Section 1.1. The results in Chapter 4 will show that the proposed method provides accurate detection of a variety of realistic weld joints in an industrial environment.

3.4.2 Initial Seed Placement

As shown in Figure 3.30, the first step is to capture stereo images of the weld joint. This weld joint detection algorithm requires that the entire weld joint is visible in both the left and right image. The adaptive line growing method is based on grayscale pixel intensities, so the images must be converted to grayscale if colour
3. Methodology

cameras are used. The initial grayscale image of the work piece is shown in Figure 3.31(a). To find the initial seed locations (step 2 in Figure 3.30), edge detection is used. The Sobel operator is used as it will detect the weld joint without including too many additional false edges from light scratches, shadows or bright spots. A binary edge image can be produced from a Sobel gradient image using Otsu’s threshold [90] which is based on the intensity distribution over the entire image. Due to the low contrast of the steel weld assemblies and the dark and bright spots produced by reflections and shadows, a global threshold will result in many of the edges being missed as shown in Figure 3.31(b). To overcome this, the edge detection threshold can be calculated locally by dividing the image into subsections. The Sobel gradient and subsequent binary threshold for each subsection can then be calculated independently. The subsections are then joined together to form the final edge image in Figure 3.31(c). Comparing Figure 3.31(b) and (c) it can be seen that more edges were detected using a local threshold method. It was found that a global binary threshold was unreliable as sometimes none of the weld joint edges being detected if the weld joint was covered in shadow.

Each edge segment in Figure 3.31(c) is then eroded to a single point located at the centre of the segment producing the initial seed locations in Figure 3.31(d). Other edge detection method such as Canny could also be used; however it was found that it would produce many more false edges due scratches and texture variations. While this will not affect the accuracy of the final result, the additional edges would increase the number of seed points and therefore increase the overall computation time.
3. Methodology

![Grayscale image](image1) ![Edge with global threshold](image2)
![Edge with local threshold](image3) ![Initial Seeds](image4)

Figure 3.31: Initial seed placement

### 3.4.3 Initial Welding Seam Line Growing Algorithm

To determine which of the initial seeds are on the weld joint and then to find the weld joint, a new line growing algorithm is developed in this thesis. It can be seen from Figure 3.31(a) that the weld joint is darker than the surrounding pixels due to the gap that is formed by joining the two pieces of steel together. Therefore the weld joint could be found by growing outwards from each seed point in the direction of the “darkest” or lowest intensity pixels. It is acceptable to assume that the weld joint is always darker than the surrounding work piece surfaces under ambient lighting conditions as there is no additional light on the joint. If the seed point is on the weld joint the line will grow in a smooth and consistent path. If the seed point is not on the weld joint and is on the background or on the surface of the steel piece, then the line will grow in an erratic and inconsistent manner as the growth will not be guided in
any particular direction as there if no line of consistently low intensity pixels to guide it.

To describe how the line growing works, the search and move directions is established in Figure 3.32. The aim of the line growing algorithm is to grow in a single pixel width line in the direction of, and along the centre of the weld joint starting from a seed point. At each current node, the algorithm decides to move across one pixel in one of eight directions based on the pixel intensities. Each current node is stored in an array known as the closed list. The direction is chosen by the directional probes $D_1, D_2, ..., D_8$. These look ahead of the current node and seek out which direction to move to based on the pixel intensity values in each direction

$$D_{sum_j} = \sum_{i=1}^{3} I_{gray}(u_{D_{i,j}},v_{D_{i,j}})$$

where $I_{gray}(u_{D_{i,j}},v_{D_{i,j}})$ is the grayscale image pixel co-ordinates of the $i^{th}$ pixel in the direction of $D_j$ and $D_{sum,j}$ is the intensity sum of all the pixels of direction $D_j$. The next current node is chosen by finding which of the eight directional probes has the lowest total pixel intensity which is given by

$$next\_node = \arg\min_j (D_{sum,j})$$

Figure 3.32: Direction Probes
3. Methodology

Looking ahead several pixels keeps the seam line growing along the weld joint. By comparison if the next node was chosen by only looking one pixel ahead based on the current nodes immediate neighbours, there is a chance that the seam line could grow out of the joint or into a dead end. To prevent the seam line from growing backwards, two more conditions are introduced. First, if the directional probes contain a previously discovered closed list node then that direction is no longer considered. The second condition is that the pixel values of $I_{\text{gray}}$ in a $3\times3$ neighbourhood around the closed list nodes are set to 255 which is the maximum intensity in a grayscale image. By doing this, the intensity sum for that directional probe becomes too high when compared to the other directions. The concept is depicted below in Figure 3.33.
3. Methodology

**Figure 3.33: Movement example**
3. Methodology

The pseudo-code for the initial line growing is given in Figure 3.34 with an example shown in Figure 3.35. In the initial line growing stage each seed point is grown over 100 iterations. The line is grown at a fixed length as we are only interested in finding which seeds are most likely to be on the weld joint. 100 iterations produces a line long enough to determine if it is in a joint, scratch or on the surface of the table or steel work piece. The results for the example in Figure 3.31 are shown in Figure 3.36.

Pseudocode for initial weld seam line growing (texts following the % are comments)

for i = 1 to number of seeds
   while j < 100 %test for 100 pixels
      if j = 1
         current_node = seed(i)
      end if
      Calculate Direction probe sums
      %Disregard direction probes that contain previously visited nodes
      if closed_list(1 to j) contains previously visited node
         Set corresponding Direction probe to null
      end if
      %Find next node to move to
      Set closed_list(j) to minimum Direction probe sum
      Set current_node(j) to closed_list(j)
      %Apply the move backwards penalty to previous closed_list nodes
      if j > 1
         Set pixel intensity of 3x3 neighbourhood at previous current node to 255
      end if
      Increment j
   end while
   initial_seam_line(i) = closed_list(i)
end for

Figure 3.34: Pseudo code for initial line growing
3. Methodology

Figure 3.35: Initial region grow example

Figure 3.36: Initial region growing results
3. Methodology

As seen by the results in Figure 3.36, the seeds that were not on an actual edge or weld joint have produced erratic lines, while those that were on the weld joint or a dark edge have grown in a smooth line. In order to remove the erratic regions they are segmented by using a smoothness threshold. During the region growing stage the number of direction changes over the growth period is recorded for each line. For example if the line moves in direction 1 followed by direction 2, then the direction count is 2. If the line moves from direction 1 followed by direction 1 again the direction count remains at 1 and so on. Lines that grow along the weld joint should grow in a fairly smooth manner without many direction changes over 100 iterations. Therefore all lines with a direction change total greater than or equal to 4 are removed. A direction change of 4 was chosen as the maximum number of direction changes for a seam line to follow a straight line, corner or curve is 4. Lines with direction changes greater than 4 are no longer assumed to be growing within the weld joint. The results are shown in Figure 3.37.

![Initial region growing results after the direction change threshold](image1)

![Remaining initial seed locations after the direction change threshold](image2)

*Figure 3.37: a) Initial region growing results after the direction change threshold b) remaining initial seed locations after the direction change threshold*
3. Methodology

3.4.4 Calculating the final Seed Location

In Figure 3.35, there are some remaining seed points that are not on the actual weld joint. This is expected as the workbench in background contains grooves that have a similar appearance to a weld joint from a local pixel intensity point of view. As these seeds cannot be differentiated based on pixel intensity alone, then the known geometry of the workspace can be used to remove the false seeds. For a calibrated stereo vision system it is possible to use triangulation to determine the 3D co-ordinates of matching pixels from two or more images. Because the height of the workbench is known, it is possible to find which seed points are on the work bench and exclude them from the search.

In this thesis, the eye-in-hand stereo vision system is calibrated using the method described in Section 3.1 which enables the calculation of the 3D co-ordinates of matching points to be determined in the robot’s base co-ordinate system. Although it was stated earlier that NCC can be unreliable for image matching of weld joints, it can be made more reliable for this application. NCC with stereo rectified images is used to determine the matching pixel in one image to a reference pixel in the other. Rectified images are used to simplify the search. Because the horizontal axes are aligned in stereo rectified images, the search is reduced to a one dimension scan line. The rectification algorithm given in [85] is used to align the images. The left image is used as a reference during seam detection in the left image and vice versa when the seam is being detected in the right image. NCC will be used to match three points on each of the initial seam lines to obtain the height of the line. If at least one of three points is matched correctly according to a height threshold, then it is assumed that the whole line is a correct match. A secondary condition based on pixel reprojection error is used to confirm the results of the height threshold.

The initial seam lines produced in Section 3.4.3 that are shown in Figure 3.37 (a) are used as the reference pixels. Each of the initial seam lines are down sampled to three points: start, middle and end.

\[ S_{pi} = \{(u_{start}, v_{start})_i, (u_{mid}, v_{mid})_i, (u_{end}, v_{end})_i\} \]  \hspace{1cm} (3.72)
3. Methodology

where $S_{p_i}$ is an array containing the down sampled initial seam line co-ordinates that will be used as reference pixels, $(x_{start}, y_{start})_i$, $(x_{mid}, y_{mid})_i$, and $(x_{end}, y_{end})_i$, are the start, middle and end points of the initial seam line contained in $S_p$.

The 3D co-ordinates for the matched image co-ordinates can be calculated in the robots base co-ordinate frame using Equation 3.69. For each initial seam line given by Equation 3.72, the 3D co-ordinates are given as

$$ P_{seam} = [(X_{Rstart}, Y_{Rstart}, Z_{Rstart})_i, (X_{Rmid}, Y_{Rmid}, Z_{Rmid})_i, (X_{Rend}, Y_{Rend}, Z_{Rend})_i] $$

(3.73)

Once the 3D positions of the initial seam lines are determined, it is then possible to remove those that are on the background by comparing their height to the height of the work bench in the robot base frame.

$$ S'_{p_i} = \begin{cases} S_{p_i} & \text{if } (Z_{seam_i} > Z_{table}) \land (Z_{seam_i} < Z_{workingrange}) \Rightarrow \text{TRUE} \\ \text{null} & \text{otherwise} \end{cases} $$

(3.74)

$$ Z_{workingrange} = |Z_{camera} - Z_{table} - Z_{torch}| $$

(3.75)

$$ Z_{seam} = (Z_{Rstart} \land Z_{Rmid} \land Z_{Rend}) $$

(3.76)

where $S'_{p_i}$ is the new array containing only the initial seam lines that comply with Equation 3.74, $Z_{table}$ and $Z_{camera}$ are the heights of the table and left camera in the robot base frame respectively and $Z_{torch}$ is the length of the welding torch from the robot wrist flange. $Z_{workingrange}$ is defined as the maximum height from the bench top that a weld joint is likely to be detected. For example if the images are captured from about 500mm above the table, and the cameras are mounted about 300mm above the tip of the welding torch this leaves a range of around 200mm from the bench surface which we expect to find the weld joint. The height of the work bench is obtained from the setup. The height of the camera is known from camera calibration, and the length of the torch is given by the manufacturer specifications. “$\land$” is the logical AND operator and “TRUE” is the logical ‘TRUE’.
3. Methodology

Equation 3.76 states that at least one of the three points in each of the initial seam lines must comply with the conditions in Equation 3.74. This is because of the unreliability for cross correlation to obtain a correct match. By using this approach it improves the probability that the correct seam lines will be retained.

Given that cross correlation can be unreliable a further check is carried out. The calculated 3D co-ordinates of the matched points can be reprojected back to the corresponding reference pixel. If the points were matched correctly, then the distance between the true reference pixel and the reprojected pixel will be relatively small. Given the 3D co-ordinates in the World frame and the camera projection matrix the reference pixel can be calculated as

$$
\begin{bmatrix}
    u_b \\
v_b \\
1
\end{bmatrix}
= M
\begin{bmatrix}
    X_w \\
Y_w \\
Z_w \\
1
\end{bmatrix}
$$

(3.77)

where \( u_b, v_b \) is the reprojected reference pixel, \( w \) is a scale factor, \( M \) is the camera projection matrix. Therefore, the reprojection error is calculated as

$$
E_i = \left[ (u_{b_{\text{start}}} - u_{\text{start}}) + (v_{b_{\text{start}}} - v_{\text{start}}) \right] + \left[ (u_{b_{\text{mid}}} - u_{\text{mid}}) + (v_{b_{\text{mid}}} - v_{\text{mid}}) \right] + \left[ (u_{b_{\text{end}}} - u_{\text{end}}) + (v_{b_{\text{end}}} - v_{\text{end}}) \right]
$$

(3.78)

where \( E_i \) is an array containing the distances between the reference pixel \((u,v)\) and the reprojected reference pixels \((u_b,v_b)\) for the start, middle and end of each initial seam line. If the reprojection error is more than 1 pixel in the \( u \) and \( v \) axes over the three seam line points, then it is removed from the initial seam list. Therefore the sum of error \( \sum E_i \) should be less than or equal to 6 which allows for at most 1 pixel error on the \( u \) and \( v \) direction for the 3 test points. The results for the example in Figure 3.36 are shown below in Figure 3.38(a).
3. Methodology

\[ S_{p_i}^* = \begin{cases} S'_{p_i} & \sum E_i \leq 6 \\ \text{null} & \text{otherwise} \end{cases} \]  

(3.79)

where \( S_{p_i}^* \) is an array containing the final seam line points that are most likely to be on the weld joint.

![Image](image1.png)

\[ \text{Figure 3.38: a) Initial seam lines after threshold b) corresponding seed points for the seam lines in a)} \]

It can be seen in Figure 3.38 (a) that the remaining seed points are all on the weld joint, the last step is to select the best seed for the final line growing stage. It should be the seed that is placed closest to the centre of the weld joint. This can be determined by examining the grayscale pixel intensities in a 3×3 neighbourhood around each seed point. Seeds closer to the centre of the joint will have lower intensity pixels around it as opposed to seeds on the edge of the joint. Therefore the seed point with the lowest total pixel intensity for its neighbourhood is selected as the final seed. The result is shown in Figures 3.39.
3. Methodology

3.4.5 Final Welding Seam Algorithm

3.4.5.1 Overview of final line growing stage

The final seam line is determined using a line growing algorithm developed in this thesis which is similar to the algorithm developed in Section 3.4.3 with a few additions. In the initial region growing stage, the line was only grown in a single direction from the seed. Since the final seed can be located anywhere on the weld joint, the final line growing algorithm is grown in two directions so that the entire weld joint is detected. Secondly, the initial line growing had a set growth of 100 iterations. As the length of the weld joint is not known the growth is not limited and therefore must stop automatically when it reaches the end of the weld joint. The direction count threshold of 4 (Section 3.4.3) is used to determine when the line has grown outside of the weld joint. Once the line reaches the end of the joint, it will not grow in smooth line as explained in Section 3.4.3 and therefore the growing can be stopped. Once the line has finished growing in the first direction, it then starts again.
3. Methodology

from the seed point in the opposite direction. The final stage is to trim the ends of the lines until the seam line coincides with the ends of the weld joint.

3.4.5.2 Edge Tolerance

The line growing is based on the assumption that the weld joint will be a continuous line of lower pixel intensity values than the steel plates on either side of the joint. There may be instances where the weld joint may not have a continuous line of dark pixels due to gaps that may be caused by lighting, scratches or markings on the steel. These imperfections cause areas of higher pixel intensities forming gaps that separate the line of dark weld joint pixels. An example is shown in Figure 3.40.

![Figure 3.40: Weld joint gap](image)

To enable the line growing to cross the gaps an edge tolerance is introduced. The edge tolerance works by analysing an edge image in a ROI around the current node at each step. The ROI is 10 x 10 pixels in size. This size is sufficient to encompass a fillet weld joint which is typically no more than 0.5-1mm which translates to be 4-5 pixels wide within the working range of the camera which is around 400-500mm above the table in this thesis. A 10x10 ROI allows a large enough window to see "ahead" of the current node. Before edge detection, the grayscale image within the
ROI is smoothed to remove false edges associated with small scratches or reflections. To preserve enough information to find the dominant edges which are associated with the weld joint an average filter is used. The average filter was found to perform better at this task than a median filter which preserved many more noisy edges. The canny edge detection is then used to find the weld joint. An example of the ROI and edge detection is shown in Figure 3.41.

![Figure 3.41: Edge tolerance ROI and edge detection](image)

Even though the image was smoothed prior to edge detection it can be seen in Figure 3.41 that additional edges caused by scratches on the surface of the steel can still appear. Therefore, the correct edges must be identified. The weld joint can be identified as two parallel edges. To identify edge segments with these properties, Hough lines can be used. The Hough line algorithm for straight lines is used for both straight and curved weld joints, as the edges for both will appear as straight lines in the ROI which is only 10x10 pixels.

For each ROI edge image, the Hough lines are calculated. As can be seen by Figure 3.42(a), each edge has an associated Hough line. The next step is to determine which Hough lines are parallel to each other. This is achieved by comparing the angle of each Hough line to the others and grouping those that have a similar angle according to a threshold. A threshold is required as it is difficult for any two Hough lines to be exactly parallel due to the profile of the edge lines returned from edge detection. It was found that tolerance of 10 degrees between edge lines was suitable.
3. Methodology

It was found through experimentation that for values less than 10 degrees, there are instances where edge lines that should be calculated as parallel are not identified due to the shape of edge lines returned by edge detection. Similarly, for values greater than 10 degrees there is a chance that edges that are not parallel will be identified as parallel.

![Figure 3.42: a) Hough lines b) parallel edge lines c) midpoint pixels used for tolerance](image)

As shown in Figure 3.42(b), additional parallel edge lines that are not part of the weld joint have been detected. It could be argued that these could be removed by assuming that the weld joint edges would be the longest as is the case in this example. However this may not always be the case due to the performance of edge detection in varying light conditions and the strength of the edges in a grayscale image. Therefore, it is assumed that any set of parallel edges should be considered as the weld joint for the edge tolerance.

With all sets of parallel edges determined, the pixels at the midpoint between them are set as the edge tolerance points as shown in Figure 3.42(c). By setting the pixels between the edges of the weld joint as the tolerance pixels will keep the line growing within the weld joint. The tolerance is set by altering the grayscale values of these pixels to a lower intensity according to the condition below.

\[
I_{\text{gray}}(u_{\text{tolerance}}, v_{\text{tolerance}}) = 0.95I_{\text{gray}}(u_{\text{tolerance}}, v_{\text{tolerance}})
\]  

(3.80)
3. Methodology

where \((u_{tolerance}, v_{tolerance})\) are the pixel co-ordinates of the tolerance point. The edge tolerance threshold is set to 95% of the original grayscale value for the tolerance pixels. The aim of the edge tolerance is to assist the line growing algorithm to span small gaps in the weld joint caused by lighting and scratches by making the original grayscale values of the edge tolerance points “darker”. It is not intended to heavily influence the direction of growth. The direction of growth is still mainly influenced by the original grayscale pixel intensities of the image. If the value were to be set too dark there is a chance that the line growing could start growing outside weld joint due to false positives as seen above in Figure 3.42(b).

3.4.5.3 End Trimming

Similar to the initial line growing algorithm, the end condition of growing is determined by the number of direction changes. While the seam line is growing within the weld joint, the number of direction changes will remain minimal. Accounting for corners and curves, the number of direction changes should be no more than 4. Once the line growing comes to the end of the weld joint, the number of direction changes will increase as the line growing has no particular direction to follow. At this point the line growing stops and the seam line has been detected. However as can be seen in Figure 3.43, the ends of the seam line must be trimmed so that the ends of the line coincide with the ends of the weld joint.

![Seam line before end trimming](image)

*Figure 3.43: Seam line before end trimming*
3. Methodology

The end trimming overview is shown below in Figure 3.44. After the seam line has been detected the ends are first trimmed using the geometry of the edges. A second trimming algorithm is used to check if further trimming is required. The second check is based on the pixel intensities.

**Figure 3.44: End trimming overview**

**Step 1: Edge Geometry**

The first stage of end trimming is based on the geometry of the weld joint. By using the stereo vision setup, the length of binary edge segments close to the weld joint can be estimated in millimetres. By determining which edges belong to the weld joint the seam line can be trimmed back to coincide with them.

The first step is to obtain a binary edge image of the global image. For this, the canny operator is selected. Canny edge detection is a robust method and will return most of the edges in an image; although it is susceptible to noise. In this case, additional edges returned by noise are not an issue as only edges that are within a very close proximity to the seam line are considered. The results of the canny edge detection are shown in Figure 3.45 with the seam line superimposed.
3. Methodology

Next, the edge pixels in the global canny edge image $I_{canny}$ that are within close proximity to the untrimmed seam line $S_u$ are extracted using the threshold below

$$I_{prox\_edges} = \begin{cases} 
1 & |I_{canny} - S_u| \leq T_p \\
0 & \text{otherwise}
\end{cases} \quad (3.81)$$

where $T_p$ is the proximity threshold in pixels and $I_{prox\_edges}$ is the edge image produced by Equation 3.81. Given that the seam line grows accurately within the weld joint and in such close proximity to the edges of the weld joint, a proximity threshold of no more than a few pixels is required in most situations. The only time a larger threshold would be required is when the weld joint is much wider due to some type of edge preparation on the weld joint. As can be seen by the results in Figure 3.45, the longest edges within the proximity threshold can be clearly identified as the edges of the weld joint. The shorter edge segments as seen on the left end of Figure 3.46 are clearly not part of the weld joint. They are scratches, textural noise or unimportant edges. To distinguish between the actual weld joint edges and scratches, a length threshold can be used. The length threshold should be in real world measurements such as millimetres. For example, the welding joint in most cases is more than 20mm long while scratches or noise may only be a few millimetres long.
A threshold in millimetres is more intuitive and repeatable than using threshold based on the number of pixels.

![Figure 3.46: Edge proximity image](image)

The remaining pixels in $I_{\text{prox_edges}}$ are grouped into line segments by calculating all the 8-connected groups of pixels. The length of each line segment in $\text{mm}$ can be calculated using the pixel co-ordinates of the line end points as follows

$$
\begin{bmatrix}
  u_{\text{start}} \\
  v_{\text{start}} \\
  1
\end{bmatrix}
= M
\begin{bmatrix}
  X_{\text{start}} \\
  Y_{\text{start}} \\
  Z_{\text{start}} \\
  1
\end{bmatrix}
\tag{3.82}
$$

$$
\begin{bmatrix}
  u_{\text{end}} \\
  v_{\text{end}} \\
  1
\end{bmatrix}
= M
\begin{bmatrix}
  X_{\text{end}} \\
  Y_{\text{end}} \\
  Z_{\text{end}} \\
  1
\end{bmatrix}
\tag{3.83}
$$

where $M$ is the 3x4 camera projection matrix with elements $M_{ij}$ at the $i^{th}$ row and $j^{th}$ column. $(u_{\text{start}}, v_{\text{start}})$, $(u_{\text{end}}, v_{\text{end}})$ are the start and end pixel co-ordinates of each line segment respectively. $[X_{\text{start}}, Y_{\text{start}}, Z_{\text{start}}]$ and $[X_{\text{end}}, Y_{\text{end}}, Z_{\text{end}}]$ are the 3D co-ordinates
of the start and end points. Equations 3.82 and 3.83 allows for the calculation of the 3D co-ordinates as

\[
\begin{bmatrix}
  w_{start} \\
  X_{start} \\
  Y_{start}
\end{bmatrix} = \begin{bmatrix}
  (u_{start} - M_{11} - M_{12})/(M_{13}Z_{start} + M_{14}) \\
  (v_{start} - M_{21} - M_{22})/(M_{23}Z_{start} + M_{14}) \\
  (1 - M_{31} - M_{32})/(M_{33}Z_{start} + 1)
\end{bmatrix}
\] (3.84)

\[
\begin{bmatrix}
  w_{end} \\
  X_{end} \\
  Y_{end}
\end{bmatrix} = \begin{bmatrix}
  (u_{end} - M_{11} - M_{12})/(M_{13}Z_{end} + M_{14}) \\
  (v_{end} - M_{21} - M_{22})/(M_{23}Z_{end} + M_{14}) \\
  (1 - M_{31} - M_{32})/(M_{33}Z_{end} + 1)
\end{bmatrix}
\] (3.85)

From Equations 3.84 and 3.85, it can be seen that the \(X\) and \(Y\) co-ordinates can be calculated if \(Z\) is known. The depth \(Z\), can be approximated by using the height of the work bench. With the 3D co-ordinates of the line ends known, their length is then estimated by

\[
L_{lines} = \sqrt{(X_{start} - X_{end})^2 + (Y_{start} - Y_{end})^2}
\] (3.86)

Therefore the lines can be segmented as follows

\[
L_{weld} = \begin{cases} 
  L_{lines} & L_{lines} \geq T_L \\
  null & otherwise
\end{cases}
\] (3.87)

where \(L_{weld}\) is an array containing the line segments that are considered most likely to be the weld joint. The weld seam is them trimmed back to weld joint lines. The results are shown in Figure 3.47.

\[
S_{trim} = \begin{cases} 
  S_u & \left|S_u - L_{lines}\right| \leq 1 \\
  null & otherwise
\end{cases}
\] (3.88)
3. Methodology

![Trimmed weld seam](image)

*Figure 3.47: Trimmed weld seam*

**Step 2: Intensity and Texture**

As a secondary measure to ensure that the ends of the weld seam are trimmed correctly, a pixel intensity and texture threshold is used. This end trimming algorithm is used immediately after the edge geometry trimming algorithm in the previous section. The same principal that is used for line growing is applied to end trimming. The principal is that the pixel intensities within the weld joint will be less than the surrounding pixels. Similarly if we look at the distribution of pixel intensity in the neighbourhood around the weld seam nodes within the weld joint there will be a distinguishable variation when compared to the nodes that are not in the weld joint. The variation is due to the fact that the centre of the weld joint will have lower intensity pixels than those closer to the steel plates either side of the weld joint. Similarly the variation of pixel intensities on the surface of the steel plate or work bench will be relatively small as there is little change in pixel intensities. These variations can be used to help distinguish the weld joint by using a range filter [96].

A range filter is used in texture analysis of images and works by replacing the intensity value of each pixel with the difference between the maximum and minimum values within a surrounding neighbourhood.
3. Methodology

Let \( I_{seam,i} \) be the grayscale intensity values of all the remaining weld seam nodes after the first end trimming stage and \( N \) is the total number of weld seam line points. Similarly, let \( R_{seam,i} \) be the range values of the remaining weld seam pixels, then the average values are calculated as

\[
\bar{P}_{seam} = \frac{1}{N} \sum_{i=1}^{N} I_{seam,i} \tag{3.89}
\]

\[
\bar{R}_{seam} = \frac{1}{N} \sum_{i=1}^{N} R_{seam,i} \tag{3.90}
\]

where \( N \) is the number of weld seam points, \( \bar{P}_{seam} \) and \( \bar{R}_{seam} \) are the average pixel intensity and pixel range of the weld seam respectively.

The threshold is then applied at both ends of the weld seam and removing one node at time. There are two exit conditions. The first is the intensity and texture thresholds; the second condition is a backup to ensure the seam line is not over trimmed due to uneven pixel intensities such as bright spots etc. Equation 3.87 is used again to find edge lines that are definitely the seam weld joint by setting \( T_L \) to a higher value. For example, from setup it easy to determine that the weld joint is longer than 20mm. Therefore if \( T_{Lmax} = 20mm \) any edge line greater than or equal to 20mm can be considered part of the weld joint. When the intensity/texture trimming reaches a node within 1 pixel of the edge lines that meet the conditions of \( T_{Lmax} \), the trimming is stopped.
3. Methodology

The Pseudo code for the final weld seam line growing algorithm is given below in Figure 3.48.

```
Pseudocode for final weld seam line growing (texts following the % are comments)
Init exit_flag to false
Init return_flag to false
Init direction_threshold
Init j = 1
while exit_flag is false
    if j = 1
        current_node = seed
    end if
    Calculate Direction probe sums
    % Disregard direction probes that contain previously visited nodes
    if closed_list(1 to j) contains previously visited node
        Set corresponding Direction probe to null
    end if
    %Find next node to move to
    Set closed_list(j) to minimum Direction probe sum
    Set current_node(j) to closed_list(j)
    if new direction
        Increment direction_threshold
    end if
    %Apply the move backwards penalty to previous closed_list nodes
    if j > 1
        Set pixel intensity of 3x3 neighbourhood at previous current node to 255
    end if
    %End of first line growing direction, return to seed and start again
    if sum(direction_threshold) >= 4 %Direction change
        current_node(j) = seed
        Set direction_threshold to zero
        Set return_flag to true
    end if
    %End of second line growing, seam line found
    if sum(direction_threshold) >= 4 and return_flag = true %Direction change
        Set exit_flag to true
    end if
    Increment j
end while
Set Weld_seam_untrimmed as closedlist
Calculate Edge_Geometry_Trim %trim step 1
Calculate Intensity_Texture_Trim %trim step 2
Calculate Final_weld_seam
```

Figure 3.48: Pseudo code for Final weld seam line growing
3. Methodology

3.5 Image Matching for the Combined Planar and Non Planar Weld Joints

3.5.1 Introduction

Weld seam line image matching can be achieved by finding the intersection of the epipolar line and seam line. This method is adopted with additional constraints to make it robust for a wider range of scenarios. The problem of multiple intersections is addressed by using known information about the workspace and camera position to estimate the correct match based on its real world co-ordinates.

The seam line is detected in the left and right images using the algorithm described in Section 3.4, then by using the seam line co-ordinates in the left image as reference, a set of matching pixels in the right image can be estimated by finding the intersection between the epipolar line and the seam line in the right image. The correct match from the initial set of intersection points is obtained using three conditions. The first is to calculate the reprojection error of initial matches back to the reference point using their calculated 3D co-ordinates. The second is a height threshold. For an incorrect match, the error in the calculated height is likely to be excessive. If the height of the table and the height that the image is taken from are known, then the height of the weld joint must be between the two. If the calculated height is less than the table height or greater than the height of the camera, it can be considered as an incorrect match. The third condition is to compare the calculated height with the height of the previous point. If we choose reference points in the left image that are close to each other, e.g. 20 pixels apart, then the change in height between consecutive weld joint points is going to be small.

3.5.2 Reference Point Selection

The first step in the matching process is to select the reference points from the seam line in the left image. As mentioned, the reference points are chosen close to each other. The start and end points are given by the seam line and the intermediate
waypoints are calculated by dividing the seam line into equal spaced points at 20 pixel intervals.

3.5.3 Intersection Points

For a calibrated stereo vision system, the epipolar line $L_{er}$ in the right image can be calculated by

$$L_{er} = F [u_{i} \ v_{i} \ 1]^T$$

(3.91)

where $F$ is the fundamental matrix and $[u_{i} \ v_{i} \ 1]^T$ are the homogenous pixel co-ordinates of the reference pixel in the left image and superscript $T$ is the matrix transpose. All seam line pixels that are within the intersection radius $R$ of the epipolar line and seam line are then calculated using

$$Q_p = \begin{cases} S_{right}(u_r, v_r) & |L_{er} - S_{right}(u_r, v_r)| \leq R \\ \text{null} & \text{otherwise} \end{cases}$$

(3.92)

where $Q_p$ is an array containing all the putative matching pixels in the right image within the intersection radius $R$, $S_{right}$ is the seam line in the right image containing pixel co-ordinates $(u_r, v_r)$. An example is shown in Figure 3.49.

![Figure 3.49: Multiple intersection example](image)
3. Methodology

3.5.3 Matching Criteria - Single Intersection

If the epipolar line intersects the seam line once, then the correct match is found using the reprojection error in a similar way in Section 3.4.4. This is achieved by calculating the 3D position for all putative matches and then using these to estimate the co-ordinates of the corresponding reference pixel in the left image. The pixel with the smallest reprojection error is considered to be the correct match and is given by

\[
\begin{bmatrix}
  u_{pl} \\
  v_{pl} \\
  1
\end{bmatrix}
= M_{CL}
\begin{bmatrix}
  X_{wp} \\
  Y_{wp} \\
  Z_{wp} \\
  1
\end{bmatrix}
\]  (3.93)

where \((X_{wp}, Y_{wp}, Z_{wp})\) are the 3D co-ordinates calculated by triangulation using the reference pixel \((u_{reference}, v_{reference})\) in the left image and the initial matches in the right image \((Q_p)\), \(M_{CL}\) is the left camera projection matrix and \((u_{pl}, v_{pl})\) are the estimated co-ordinates for the reference pixel based on the initial putative matches. Therefore for the single intersection scenario the matching pixel in the right image \((u_{match_r}, v_{match_r})\) is calculated by finding the reprojected estimate with the smallest distance from the reference pixel such that

\[
Q_{match(u_{match_r}, v_{match_r})} = \arg \min_i ((u_{pl_i}, v_{pl_i}) - (u_{reference}, v_{reference}))
\]  (3.94)

where \((u_{pl_i}, v_{pl_i})\) is the estimated pixel co-ordinate of the reference pixel in the left image of the \(i^{th}\) putative match given by Equation 3.92.

3.5.4 Matching Criteria - Multiple Intersections

For non-trivial scenario of multiple intersections, Equation 3.94 will not have a unique solution. Therefore using pixel co-ordinates alone will result in the likelihood of a false match. If points are incorrectly matched, then the calculated heights will usually be some unrealistic value. Since the height of the table is known, and the
heights of the cameras are known, then the height of the correct match must lie somewhere between the two. Secondly, if the waypoints are chosen to be close to each other, then we can compare the calculated heights with the height of the previous correct match.

\[
Q_{p(u,v)} = \begin{cases} 
S_{\text{right}(u,v)} & (Z_{Wp(u,v)} \leq Z_{\text{max}}) \lor (Z_{Wp(u,v)} \geq Z_{\text{table}}) \lor (Z_{Wp(u,v)} - Z_{(\text{match}_r-1)}) \leq Z_T = \text{TRUE} \\
null & \text{otherwise} 
\end{cases}
\]

(3.95)

where \(Z_{\text{camera}}\) is the height of the camera, \(Z_{\text{table}}\) is height of the table and \(Z_T\) is height change threshold between the current seam line points \(Z_{Wp(u,v)}\) and the previously matched seam line point \(Z_{(\text{match}_r-1)}\), and “\(\text{TRUE}\)” is the logical ‘TRUE’. This will narrow the initial matches down to a set of possible matches around one of the intersection points between the epipolar line and seam line. From there the correct match can be found using Equation 3.94.

**3.6 Summary**

The welding environment presents many unique challenges for computer vision such as reflections from metallic surfaces, imperfections on the work piece surface such as rust, mill scale and scratches which are not randomly placed from work piece to work piece. The work pieces can also have a variety of surface finishes and base material such as paint, steel and aluminium which will affect contrast of the weld joint and increase or decrease the effects of reflections. Furthermore, image matching and triangulation of weld joints cannot be solved using traditional methods as weld joints are typically considered to be both featureless and textureless. Therefore computer vision algorithms specific to the welding environment must be developed.

The methods developed in this thesis have filled the gaps in key steps 1-4 for the development of an autonomous robot arc welding system as identified in Section 1.1. In particular the development of autonomous, accurate and reliable robot manipulator
and eye-in-hand stereo vision calibration, weld joint identification and localisation methods. These methods not only provide a practical solution for industry, but important contributions for the robust use of computer vision in welding environments.

The weld joint detection algorithms introduced in this thesis provide the first method capable of identifying realistic welding joints for both planar and non-planar fillet and butt welds regardless of the base material, surface imperfections and surface finish for industrial applications. The weld joints can be identified in the image without a ROI or prior knowledge of the location of the weld joint in the image and is not reliant high contrast between the background and foreground such as aluminium or stainless steel on a dark background. While both of the proposed methods are capable of detecting any shape weld joint, the planar weld joint detection is limited to mild steel work pieces with straight line boundaries due to the background subtraction method. However the combined planar and non-planar weld joint detection does not rely on the shape of the work piece boundary and can be used for any work piece shape and base material in a well-lit environment which will be demonstrated in Chapter 4.

For weld joint localisation, the image matching methods developed in this thesis provide a solution to the image matching of weld joints which are not dependent on feature matching using pixel intensities or texture. The optimised robot and hand-eye calibration method is capable of achieving sub-millimetre localisation of the weld joint using only the hand mounted stereo cameras, mechanical pointer and calibration board. The development of an accurate calibration method for the robot and eye-in-hand stereo vision cameras without using expensive 3D co-ordinate measuring devices or laser scanners makes it highly desirable for industrial applications.

The experimental results in Chapter 4 will demonstrate that the methods developed in this thesis have provided accurate, robust and reliable solutions for the development of an autonomous robotic arc welding system.
Chapter 4  Results and Discussion

4.1 Experimental Setup

The experiments were conducted using a Fanuc ArcMate 100iC, 6 axis industrial robot with a repeatability accuracy of ± 0.08mm. The robot is fitted with a Binzel Abiob A360 welding torch and Lincoln Electric PowerWave F355i welding power source. The stereo vision system consisted of two off the shelf uEye USB colour CCD cameras (resolution 1280×1024). The cameras are attached to the welding torch as shown in Figure 4.1. The work bench is an industrial grade Demmeler welding bench with a machined steel surface. The experiments were conducted in a well-lit environment. The work pieces were placed in an arbitrary position on the table top. The robot was manually jogged using the teach pendant to capture the images.

Figure 4.1: Experimental setup
4. Results

4.2 Optimised Robot and Hand-Eye Calibration Results

4.2.1 Calibration Setup

The calibration board (Figure 3.5) is placed on the workbench in front of the robot as shown below in Figure 4.2. The TCP is setup using the six-point method as per the robot manufacturer’s instructions [97]. However it should be noted that the accuracy of the TCP setup plays a critical role to the overall accuracy of the robot and hand-eye calibration. To ensure accuracy, the precision pointer shown in Figure 3.3 is used instead of the welding wire to guarantee a consistent reference point during the TCP setup. By using the precision pointer instead of the welding wire, the TCP accuracy is kept to within the ±0.5mm recommended in [50].

The images captured during the intrinsic and hand-eye calibration stages are taken from approximately 300-400mm above the calibration board in various positions within the robot’s working envelope. This height range is specified by the camera manufacturer as the optimal working range for the best accuracy. As this is the optimal working range of the cameras all subsequent images of the welding work pieces are taken from within the same height range.

Figure 4.2: Calibration setup

120
4. Results

4.2.2 Camera Intrinsic Parameter Calibration Results

The left and right camera intrinsic parameters were calculated using [13] with the proposed automatic grid detection method. Each camera was calibrated using a set of 30 images each (60 images in total). The calibration images for the left and right cameras are captured simultaneously. It was found by experimentation that using 30 images for each camera allowed for the calibration board to cover most of image plane. This allowed for more accurate estimations of the distortion co-efficients and improved mapping between the image plane and camera frame. The full set of intrinsic calibration images are shown in Figures 4.3 and 4.4.

Figure 4.3: 30 images used for the left camera intrinsic parameter calibration
4. Results

*Figure 4.4: 30 images used for the right camera intrinsic parameter calibration*

The automatic calibration experiment was conducted using a 2.4 GHz Intel i5 Processor. The results in Table 1 show that the automatic method has a much faster processing time than the standard method. Over the full set of 60 images the automated method reduced the calibration time by 62%.

It is also important to note that manually selecting the corners of the calibration board using the standard method is dependent on the speed and competence of the operator. In an industrial environment, if manual calibration is required it would add further expense in addition to the downtime of the machine as a trained operator would be required to carry out the calibration procedure. Even then the time and quality of the calibration will vary depending on the competence of the trained operator.
4. Results

Table 1: Camera Intrinsic Parameter Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Standard</th>
<th>Automatic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>left</td>
<td>right</td>
</tr>
<tr>
<td>$F_u, F_v$</td>
<td>1783.361,1783.299</td>
<td>1787.167,1787.148</td>
</tr>
<tr>
<td>$u_0, v_0$</td>
<td>600.956,494.593</td>
<td>642.374,505.743</td>
</tr>
<tr>
<td>$\alpha_c$</td>
<td>0.00119</td>
<td>0.00106</td>
</tr>
<tr>
<td>$k_1, k_2$</td>
<td>-0.128,0.271</td>
<td>-0.113,0.213</td>
</tr>
<tr>
<td>Pixel Error</td>
<td>0.146,0.145</td>
<td>0.196,0.187</td>
</tr>
<tr>
<td>Avg. Time</td>
<td>19.3 seconds/image</td>
<td>7.3 seconds/image</td>
</tr>
<tr>
<td>Total Time</td>
<td>19.3 minutes (60 images)</td>
<td>7.3 minutes (60 images)</td>
</tr>
</tbody>
</table>

The intrinsic parameter matrices (Equation 2.11) for the left and right camera using the data in Table 1 can then be written as

$$ ^p K_{CL} = \begin{bmatrix} 1783.361 & 2.122 & 600.956 & 0 \\ 0 & 1783.299 & 494.593 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (4.1) $$

$$ ^p K_{CR} = \begin{bmatrix} 1787.167 & 1.894 & 642.374 & 0 \\ 0 & 1783.299 & 505.743 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (4.2) $$

4.2.3 Stereo Calibration

The transformation matrix from the left camera frame Equation (3.1) to the right camera frame was calculated using the stereo calibration procedure in [14]. The images used for stereo calibration are the same as those used for the intrinsic camera calibration.

$$ ^{CR} T_{CL} = \begin{bmatrix} 0.926 & -0.005 & -0.376 & 138.052 \\ 0.010 & 0.999 & 0.011 & 2.914 \\ 0.376 & -0.0137 & 0.926 & 28.382 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4.2) $$

123
4. Results

4.2.4 Initialisation of the Denavit-Hartenberg Parameters

The initial estimate for the robotic kinematic model was determined using the nominal measurements provided by the robot manufacturer. The geometry of the robot used in the experiments is shown below in Figures 4.5 and 4.6. The nominal DH parameters for a Fanuc ArcMate 100iC are given in Table 2.

![Figure 4.5: Robot link measurements](image-url)
4. Results

Figure 4.6: Robot axis locations [29]

Table 2: Nominal DH parameters for a Fanuc ArcMate 100iC

<table>
<thead>
<tr>
<th>Joint</th>
<th>$\theta_{\text{link } i}$</th>
<th>$\alpha_{\text{link } i}$ (deg)</th>
<th>$a_{\text{link } i}$ (mm)</th>
<th>$d_{\text{link } i}$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\theta_1$</td>
<td>-90</td>
<td>150</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>$\theta_2 + 90$</td>
<td>180</td>
<td>-600</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>$\theta_3 + \theta_2 + 180$</td>
<td>-90</td>
<td>199.94</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>$\theta_4$</td>
<td>-90</td>
<td>0</td>
<td>-640</td>
</tr>
<tr>
<td>5</td>
<td>$\theta_5$</td>
<td>-90</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>$\theta_6$</td>
<td>180</td>
<td>0</td>
<td>-100</td>
</tr>
</tbody>
</table>

4.2.4 Initialisation of the Robot-World Transformation

The initial values for the robot-world transformation are obtained using the precision pointer to touch three points on the calibration board as discussed in Section 3.1.4. The three touch points $P_1, P_2$ and $P_3$ are given in Table 3.

Table 3: Touch points for initial Robot-World transformation

<table>
<thead>
<tr>
<th></th>
<th>$X_R$ (mm)</th>
<th>$Y_R$ (mm)</th>
<th>$Z_R$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_o$</td>
<td>884.834</td>
<td>-94.359</td>
<td>2.770</td>
</tr>
<tr>
<td>$P_1$</td>
<td>1034.759</td>
<td>-94.916</td>
<td>2.467</td>
</tr>
<tr>
<td>$P_2$</td>
<td>886.325</td>
<td>116.128</td>
<td>2.670</td>
</tr>
</tbody>
</table>
4. Results

Using Equations 3.3, 3.6 and 3.7 the robot-world transformation is then calculated to be

\[
{\hat{r}}_W^T = \begin{bmatrix}
0.999 & 0.004 & 0.001 & 884.834 \\
-0.004 & 0.999 & 0.001 & -94.359 \\
-0.001 & -0.001 & 0.999 & 2.77 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]  
(4.3)

4.2.5 Initialisation of the Hand-Eye Transformation

The initial values for the hand-eye transformation from left camera to the robot flange were obtained using the average of Equation 3.11 for 15 different robot configurations within the robots workspace as discussed in Section 3.1.5. The extrinsic transformation matrix for the left camera is obtained using [14].

An additional 15 images other than those used for the intrinsic calibration were used for this process. Additional images are used as only images taken from the left camera are required. This means that there is no restriction from occlusions in the right image, which means the robot can be manoeuvred within the entire working range of the system to capture the images of the calibration board. This allows for more accurate calibration of the hand-eye transformation within the working range of the system. It was found that using 15 calibration positions provided the most accurate solution. The hand-eye calibration images for the left camera are shown in Figure 4.7.
4. Results

Figure 4.7: Hand-eye calibration images

The initial estimate for the left camera to robot flange transformation was calculated to be

$$\hat{r}_{\hat{T}} = \begin{bmatrix}
0.095 & 0.995 & 0.018 & -136.089 \\
-0.984 & 0.091 & 0.156 & -85.381 \\
0.153 & -0.033 & 0.988 & 117.891 \\
0 & 0 & 0 & 1
\end{bmatrix}$$ (4.4)

4.2.5 Optimisation Results

The optimisation algorithm was run using the “fmincon” function in MATLAB with the objective function given by Equation 3.19 subject to the non-linear constraints in Equations 3.21 to 3.29.

The thirty unknown geometrical variations in Equations 3.14, 3.15 and 3.16 are given in Tables 4, 5, and 6. There are 18 parameters for the robot kinematic model and 6 parameters each for the robot-world and hand-eye transformation which are composed of three rotation values represented by their Euler angles ($\phi, \beta, \gamma$) and three for the translation component.
4. Results

Table 4: Geometrical variations for the robot-world transformation

<table>
<thead>
<tr>
<th>Joint</th>
<th>$\Delta^R \varphi_W$ (rad)</th>
<th>$\Delta^R \beta_W$ (rad)</th>
<th>$\Delta^R \gamma_W$ (rad)</th>
<th>$\Delta^R X_W$ (mm)</th>
<th>$\Delta^R Y_W$ (mm)</th>
<th>$\Delta^R Z_W$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.000172</td>
<td>-0.010270</td>
<td>0.005166</td>
<td>0.212950</td>
<td>0.082589</td>
<td>0.388360</td>
</tr>
</tbody>
</table>

Table 5: Geometrical variations for the hand-eye transformation

<table>
<thead>
<tr>
<th>Joint</th>
<th>$\Delta^F \varphi_{CL}$ (rad)</th>
<th>$\Delta^F \beta_{CL}$ (rad)</th>
<th>$\Delta^F \gamma_{CL}$ (rad)</th>
<th>$\Delta^F X_{CL}$ (mm)</th>
<th>$\Delta^F Y_{CL}$ (mm)</th>
<th>$\Delta^F Z_{CL}$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.001295</td>
<td>-0.000050</td>
<td>0.003186</td>
<td>-0.069444</td>
<td>0.382895</td>
<td>-0.452267</td>
</tr>
</tbody>
</table>

Table 6: Tolerance variations for the robot kinematic model

<table>
<thead>
<tr>
<th>Joint</th>
<th>$\Delta \alpha_{link,i}$ (rad)</th>
<th>$\Delta a_{link,i}$ (mm)</th>
<th>$\Delta d_{link,i}$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.000557</td>
<td>0.102721</td>
<td>-0.388363</td>
</tr>
<tr>
<td>2</td>
<td>-0.000557</td>
<td>-0.089802</td>
<td>0.054081</td>
</tr>
<tr>
<td>3</td>
<td>0.000535</td>
<td>-0.402472</td>
<td>-0.054020</td>
</tr>
<tr>
<td>4</td>
<td>0.000023</td>
<td>-0.108664</td>
<td>-0.183963</td>
</tr>
<tr>
<td>5</td>
<td>0.000265</td>
<td>0.236258</td>
<td>0.104632</td>
</tr>
<tr>
<td>6</td>
<td>-0.000022</td>
<td>-0.069449</td>
<td>0.452257</td>
</tr>
</tbody>
</table>

The actual DH parameters are then given in Table 7 with the actual robot-world and hand-eye transformations after optimisation are given below.

Table 7: Actual D-H parameters after optimisation

<table>
<thead>
<tr>
<th>Joint</th>
<th>$\theta_{link,i}$</th>
<th>$\alpha_{link,i}$ (deg)</th>
<th>$a_{link,i}$ (mm)</th>
<th>$d_{link,i}$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\theta_1$</td>
<td>-90.032</td>
<td>150.1</td>
<td>-0.388</td>
</tr>
<tr>
<td>2</td>
<td>$\theta_2+90$</td>
<td>179.970</td>
<td>-600.09</td>
<td>0.054</td>
</tr>
<tr>
<td>3</td>
<td>$\theta_3+\theta_2+180$</td>
<td>-89.969</td>
<td>199.54</td>
<td>-0.054</td>
</tr>
<tr>
<td>4</td>
<td>$\theta_4$</td>
<td>-89.999</td>
<td>-0.109</td>
<td>-640.18</td>
</tr>
<tr>
<td>5</td>
<td>$\theta_5$</td>
<td>-89.985</td>
<td>0.236</td>
<td>0.104</td>
</tr>
<tr>
<td>6</td>
<td>$\theta_6$</td>
<td>180</td>
<td>-0.069</td>
<td>-99.548</td>
</tr>
</tbody>
</table>

$$R_{T_{W\text{actual}}} = \begin{bmatrix} 0.999 & -0.001 & -0.009 & 885.05 \\ 0.001 & 1 & 0.002 & -94.276 \\ 0.009 & -0.002 & 0.999 & 3.1584 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4.5)$$
4. Results

\[
F_{CL_{\text{actual}}} = \begin{bmatrix}
0.098 & 0.995 & 0.019 & -136.160 \\
-0.983 & 0.094 & 0.157 & -84.998 \\
0.154 & -0.034 & 0.987 & 117.440 \\
0 & 0 & 0 & 1
\end{bmatrix}
\] (4.6)

4.2.6 Verification of the Calibration Accuracy

To assess the calibration accuracy, 4 sets of stereo images of the calibration board are taken within the system working range. At each robot position, the 3D co-ordinates of the calibration points are calculated in the robots base frame. The ground truth data was obtained using the robot and the precision pointer to touch each point on the calibration board and the position data obtained from the robot controller. The position error is then given by the difference between the two.

For each image capture position, the co-ordinates of the calibration points in the left camera frame are calculated by obtaining the extrinsic position of the left camera using the optimised transformations using

\[
^{CL}T_W = \{^F_{T_{CL_{\text{actual}}}}\}^{-1}\{^R_{T_{\text{actual}}}\}^{-1}_R T_{W_{\text{actual}}}
\] (4.7)

The left camera projection matrix is then given by

\[
P_{CL} = ^R P_{CL} ^{CL} T_W
\] (4.8)

The extrinsic position of the right camera is calculated using Equation 4.2 and 4.7.

\[
^{CR}T_W = ^{CR}T_{CL} ^{CL} T_W
\] (4.9)

The right camera projection matrix is then given by

\[
P_{CR} = ^R P_{CR} ^{CR} T_W
\] (4.10)
4. Results

The positions of the test points in the robot base frame are then obtained using the triangulation from Equations 2.30, 2.33, 2.34 and 3.69. The 48 test points on the calibration board are shown in Figure 4.8. The position error is then given by

\[
^{R}P_{\text{error}} = ^{R}P_{\text{calculated}} - ^{R}P_{\text{measured}}
\]  

(4.11)

![Test points](image)

*Figure 4.8: Test points*

The robot positions are given in Table 8, with the corresponding test images given in Figures 4.9, 4.10, 4.11 and 4.12. The effectiveness of the proposed calibration method is verified with significant rotation of the cameras as shown by the test images. This demonstrates that the required accuracy is retained regardless of the robot position within the working range of the system. This is particularly important for robotic welding applications as the robot will need to be manoeuvred into a wide range of different positions to take images of the weld joint.
4. Results

Table 8: Robot joint angles for calibration test positions

<table>
<thead>
<tr>
<th>Position</th>
<th>$\theta_1$ (deg)</th>
<th>$\theta_2$ (deg)</th>
<th>$\theta_3$ (deg)</th>
<th>$\theta_4$ (deg)</th>
<th>$\theta_5$ (deg)</th>
<th>$\theta_6$ (deg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position 1</td>
<td>-1.134</td>
<td>21.731</td>
<td>-11.105</td>
<td>-4384</td>
<td>-75.004</td>
<td>22.008</td>
</tr>
<tr>
<td>Position 2</td>
<td>-4.102</td>
<td>22.266</td>
<td>-10.924</td>
<td>-3.038</td>
<td>-74.113</td>
<td>4.962</td>
</tr>
<tr>
<td>Position 3</td>
<td>0.0.37</td>
<td>-12.074</td>
<td>-15.733</td>
<td>8.564</td>
<td>-42.117</td>
<td>-19.212</td>
</tr>
</tbody>
</table>

Figure 4.9: Test position 1 (left and right views)

Figure 4.10: Test position 2 (left and right views)
4. Results

The position error between the calculated and measured Cartesian co-ordinates of the 48 test points for each position is shown below in Figures 4.13, 4.14, 4.15 and 4.16. It can be seen that the proposed calibration method achieves the required accuracy of ± 1mm over the entire moving range of the robot even with significant rotation. By comparison, for an un-calibrated robot and non-optimised robot-world and hand-eye transformations results shown in Figures 4.17, 4.18, 4.19 and 4.20 it can be seen that the error is almost double, exceeding ± 2mm in all three directions which is unacceptable for robotic arc welding as not the welding wire not be in the joint which will result in defective welds.
Figure 4.13: Minimised 3D Cartesian errors for test position 1
Figure 4.14: Minimised 3D Cartesian errors for test position 2
4. Results

Figure 4.15: Minimised 3D Cartesian errors for test position 3
4. Results

Figure 4.16: Minimised 3D Cartesian errors for test position 4
4. Results

Figure 4.17: Non-minimised 3D Cartesian errors for test position 1
4. Results

Figure 4.18: Non-minimised 3D Cartesian errors for test position 2
Figure 4.19: Non-minimised 3D Cartesian errors for test position 3
Figure 4.20: Non-minimised 3D Cartesian errors for test position 4
4. Results

4.3 Butt Weld Joint Detection and Localisation Results

4.3.1 Work Piece Case Studies

The butt weld joint detection method introduced is verified by 3 case studies shown in Figures 4.21, 4.22 and 4.23. The work pieces are placed in an arbitrary position on the work bench as shown in Figure 4.24. It is important to note that the welding seams run horizontally across the image compared to vertically as seen in [53] and that the contrast and lighting vary between the views seen by the left and right camera which can be an issue for cross correlation. The left camera images are used as the reference image for matching. The weld joint detection algorithm developed in Section 3.2 is used to find the seam line in the left image. This provides both the start and end points for the weld. The intermediate way points between the weld start and weld end points are chosen based on the requirements for the robot path, i.e. the waypoint/s are chosen at the top of the arc/s, or the peaks of the saw tooth. The 3D Cartesian co-ordinates of start, end and intermediate waypoints are then calculated using the image matching method described in Section 3.3.

The effectiveness of the proposed weld joint identification method is confirmed against the well-known method introduced in [52]. The proposed image matching was also bench marked against NCC and robust homography estimation using RANSAC.
4. Results

Figure 4.21: Planar weld joint - case study 1

Figure 4.22: Planar weld joint - case study 2

Figure 4.23: Planar weld joint - case study 3
4. Results

![Experimental setup for planar weld joint detection](image)

### 4.3.2 Butt Weld Joint Detection Results

The thresholds $\beta$, $T_2$ and $T_3$ from Equations 3.58, 3.66 and 3.67 are set to 0.22, 10 and 5 respectively and the sliding window size $w$ in Equations 3.59 and 3.60 set to 7. These values were selected imperially based on experimental analysis for this particular workshop environment.

#### 4.3.2.1 Case Study 1 – Saw Tooth

The first case study is a saw tooth shaped weld joint. The saw tooth shaped joint will show that the proposed method is capable of accurately identifying both straight lines and sharp corners. The results are shown in the figures below in sequential order of the detection method given in Section 3.2. For clarity a drawing of case study 1 is shown in Figure 4.25 to indicate the weld joint location. In Figure 4.26 the boundary of the work piece is identified using Hough lines. The work piece boundary lines are then refined using the sliding windows with the result is shown in Figure 4.27. The background is then segmented from the work piece which is shown in Figure 4.28. The edge image for the segmented image is then shown in Figure 4.29. It can be seen that there are some additional edge lines produced which belong to small scratches, reflections and other imperfections on the work piece surface. These are removed using Equation 3.67 with the result shown in Figure 4.30. The
4. Results

next step is the boundary edge removal and seam line identification which is shown in Figures 4.31 and 4.32 respectively. To demonstrate the accuracy of the proposed algorithm several close ups of key areas such as corners, weld start and weld end points are shown in Figures 4.33 to 4.36.

![Weld joint](image1.png)

5mm mild steel

*Figure 4.25: Weld joint detail for case study 1*

![Hough search lines](image2.png)

*Figure 4.26: Hough search lines - case study 1*
4. Results

Figure 4.27: Refined Hough lines - case study 1 (Equation 3.66)

Figure 4.28: Back segmentation - case study 1
4. Results

Figure 4.29: Edge identification in foreground image - case study 1

Figure 4.30: Edge image after small area removal - case study 1 (Equation 3.67)
4. Results

Figure 4.31: Boundary removal - case study 1

Figure 4.32: Final seam line - case study 1
4. Results

Figure 4.33: Weld start close up - case study 1

Figure 4.34: First saw tooth peak close up - case study 1
4. Results

Figure 4.35: Second saw tooth peak close up - case study 1

Figure 4.36: Weld end close up - case study 1
4. Results

As can be seen by Figures 4.33 to 4.36 the seam line has been accurately detected in case study 1. It can be seen in Figures 4.33 and 4.26 that the seam line finishes a few pixels before the edge of the work piece at the weld start and weld end points. This is a result of the boundary removal in Section 3.2.4.3. Depending on the accuracy of the gradient edge identification in the foreground image (Section 3.2.4.1), the work piece boundary line may not be exactly on the true edge of the work piece. As a result the ends of the seam line may be trimmed off. However, the removal of a few pixels on the ends of the seam line which translates to less than a 1mm positioning error in the robot base frame at the weld start and end points. This will not affect the accuracy of the final welding results which will be given in Section 4.3.5. It should also be noted that in Figure 4.34 that the seam line also cuts the corner by a few pixels. This is again due to the accuracy of the edge identification. However as with the weld start and weld end points, an error of a few pixels will not affect the final welding results.

4.3.2.2 Case Study 2 – Curve

Case Study 2 is a curved weld joint which is chosen to demonstrate the effectiveness of the proposed methods ability to identify non straight seam lines. A drawing indicating the location of the weld joint is shown in Figure 4.37. As with the results for case study 1, the results for case study 2 are shown in the logical order of the weld joint detection algorithm as given in Section 3.2.

Figure 4.37: Weld joint detail for case study 2
4. Results

Figure 4.38: Hough search lines - case study 2

Figure 4.39: Refined Hough lines for case study 2 (Equation 3.66)
4. Results

Figure 4.40: Back segmentation - case study 2

Figure 4.41: Edge identification in foreground image - case study 2
4. Results

Figure 4.42: Edge image after small area removal - case study 2 (Equation 3.67)

Figure 4.43: Boundary removal - case study 2
4. Results

Figure 4.44: Final seam line - case study 2

Figure 4.45: Weld start close up - case study 2
4. Results

Figure 4.46: Weld seam middle close up - case study 2

Figure 4.47: Weld end close up - case study 2
4. Results

The results in Figures 4.45 to 4.47 show that the seam line has been accurately detected. As with the results from case study 1, it can be seen that the weld start and weld end points in Figures 4.45 and 4.47 are a few pixels back from the edge of the work piece, however this will not affect the accuracy of the final welded result as it translates to less than a 1mm positioning error in the robot base frame at these points.

4.3.2.3 Case Study 3 – S shape

Case Study 3 is an S shaped weld joint and is an extension of the curved joint from case study 2 to demonstrate the proposed methods accuracy to identify the entire seam line such as the top of the arcs and the inflection point inflection point which is important for robot manipulator path planning. A drawing indicating the location of the weld joint is shown in Figure 4.48. As with the two previous case studies, the results are given in sequential order of the detection algorithm as given in Section 3.2.

![Weld joint detail for case study 3](image)

*Figure 4.48: Weld joint detail for case study 3*
4. Results

Figure 4.49: Hough search lines - case study 3

Figure 4.50: Refined Hough lines - case study 3 (Equation 3.66)
4. Results

Figure 4.51: Back segmentation - case study 3

Figure 4.52: Edge identification in foreground image - case study 3
4. Results

Figure 4.53: Edge image after small area removal - case study 3 (Equation 3.67)

Figure 4.54: Boundary removal - case study 3
4. Results

Figure 4.55: Final seam line - case study 3

Figure 4.56: Weld start close up - case study 3
4. Results

Figure 4.57: First saddle point close up - case study 3

Figure 4.58: Saddle transition point close up - case study 3
4. Results

Figure 4.59: Second saddle point close up - case study 3

Figure 4.60: Weld end close up - case study 3
4. Results

The results for case study 3 show that the proposed planar butt weld joint detection method has accurately detected the seam line as shown in Figures 4.56 to 4.60. As with the results for case studies 1 and 2, it can be seen that the weld start and end points in Figures 4.56 and 4.60 are a few pixels back from the edge of the work piece; however this does not affect the accuracy of the final welded result as it translates to less than a 1mm positioning error in the robot base frame.

The results for all three case studies demonstrate that the proposed planar butt weld detection method is capable of identifying the seam line from a single image regardless of the shape of the weld joint without prior knowledge of its position in the image.

4.3.3 Butt Weld Joint Detection Comparison

A popular seam identification algorithm is used for comparison with the proposed method. The process in [52] starts with a 3x3 median filter to smooth the image, followed by sharpening using a Laplacian operator. The image is then converted to binary using an automatic threshold method. This followed by a “resting” process which removes small clusters of pixels on the surface of the work piece caused by scratches, reflections etc. This method is ideal for high contrast work pieces made of aluminium or stainless steel where there is high contrast between the work piece and weld joint as demonstrated by the example in Figure 4.61. However, as can be seen by the results for the three case studies in Figures 4.62, 4.63 and 4.64 that after the initial binary segmentation the weld joints are not visible. Therefore the method in [52] cannot be used effectively for the identification of weld joints where there is low contrast between the weld joint and the work piece. The results in the previous section demonstrate that the proposed method is capable of identifying the weld joint without the need for high contrast between the work piece and background making it a valuable alternative for the detection of weld joint for ferrous materials.
4. Results

A) Original colour image

B) Segmented image using comparison method

*Figure 4.61: Weld joint detection comparison with aluminium on dark background*
4. Results

Figure 4.62: Weld joint detection using method from [52] for case study 1 - seam line is not detected

Figure 4.63: Weld joint detection using method from [52] for case study 2 - seam line is not detected
4. Results

Figure 4.64: Weld joint detection using method from [52] for case study 3 - seam line is not detected

4.3.4 Butt Weld Joint Image Matching Results

4.3.4.1 Test points

The start, end and intermediate way points are used to demonstrate the accuracy of the proposed image matching algorithm are shown in Figure 4.65, 4.66 and 4.67 by the yellow “X” markers with the weld seam line overlayed on the image. The way points were chosen manually, as path planning is not within the scope of this thesis as explain in Chapter 3. The emphasis of this thesis is on weld joint detection and localisation which can then be adapted for path planning.
4. Results

Figure 4.65: localisation test markers - case study 1

Figure 4.66: localisation test markers - case study 2
4. Results

Figure 4.67: localisation test markers - case study 3

4.3.4.2 Proposed Homography Estimation Results

The corner points for both the left and right images were obtained from the intersections of the Hough lines used for background segmentation. The 2D homography matrices were then calculated using Equation 2.27. The transformation matrix for each set of images are given below.

\[
H_{\text{case1(proposed)}} = \begin{bmatrix}
0.6178 & -0.0287 & -139.13 \\
0.0601 & 0.5714 & -18.388 \\
0.0001 & 0 & 0.4990
\end{bmatrix}
\] (4.12)

\[
H_{\text{case2(proposed)}} = \begin{bmatrix}
-0.6229 & 0.0254 & 143.22 \\
-0.0633 & -0.5707 & 20.631 \\
-0.0001 & 0 & -0.493
\end{bmatrix}
\] (4.13)
4. Results

\[
H_{\text{case3, proposed}} = \begin{bmatrix}
-0.6221 & 0.0242 & 137.4 \\
-0.0620 & -0.5684 & 19.944 \\
-0.0001 & 0 & -0.4939
\end{bmatrix}
\] (4.14)

4.3.4.3 Comparison with Existing Methods

The image matching results using the proposed method were compared to the robust homography estimation algorithm and epipolar geometry based NCC matching. For the robust homography estimation, Harris corners are used to find feature points with NCC used to match them [98]. The feature points and inliers for the image pairs are shown in Figures 4.68, 4.69 and 4.70. The inliers were obtained using a threshold of \( T_{\text{pixels}} = 0.001 \) pixels (Equation 2.29). To ensure RANSAC estimates the homography of the weld joint plane; the background segmented images were used. For comparison with NCC matching, the method in [81] is used with a square window size of 23x23 pixels. The Fundamental matrix used to calculate the epipolar line is obtained using the calibrated cameras from Equation 2.20. The image matching errors for the respective methods are given Tables 9, 10 and 11.
4. Results

Figure 4.68: Harris feature points for case study 1. 179 putative matches with 37(21%) selected as inliers.
4. Results

![Harris corners left view](image1)

a) Harris corners left view

![Harris corners right view](image2)

b) Harris corners right view

![Matched feature points](image3)

c) Matched feature points

*Figure 4.69: Harris feature points for case study 1. 248 putative matches with 36(15%) selected as inliers.*
4. Results

Figure 4.70: Harris feature points for case study 3. 133 putative matches with 12(9%) selected as inliers.
4. Results

\[ H_{\text{case1}(\text{RANSAC})} = \begin{bmatrix} 0.6094 & -0.0259 & -136.89 \\ 0.0589 & 0.5643 & -17.595 \\ 0.0001 & 0 & 0.4975 \end{bmatrix} \] (4.15)

\[ H_{\text{case2}(\text{RANSAC})} = \begin{bmatrix} -0.6103 & 0.0308 & 139.76 \\ -0.0605 & -0.5547 & 19.036 \\ -0.0001 & 0 & -0.48623 \end{bmatrix} \] (4.16)

\[ H_{\text{case3}(\text{RANSAC})} = \begin{bmatrix} -0.5934 & 0.0301 & 126.15 \\ -0.0629 & -0.5274 & 11.197 \\ -0.0001 & 0 & -0.4896 \end{bmatrix} \] (4.17)

In Tables 9, 10 and 11, “Reference” refers to the pixel location of the point in the left image to be matched in the right image; “calculated match” is the calculated matched pixel location in the right image. “Actual” is the ground truth pixel location of the matching point in the right image and “Match Error” is the absolute difference between the calculated and the actual matching points in pixels.

**Table 9: Image matching pixel error for case study 1**

<table>
<thead>
<tr>
<th>Reference ((u,v)) pixel</th>
<th>Actual match ((u,v)) pixel</th>
<th>Calculated Match (H) proposed method ((u,v)) pixel</th>
<th>Match Error proposed ((\Delta u, \Delta v)) pixel</th>
<th>Calculated Match NCC ((u,v)) pixel</th>
<th>Match Error NCC ((\Delta u, \Delta v)) pixel</th>
<th>Calculated Match (H) estimated with RANSAC ((u,v)) pixel</th>
<th>Match Error RANSAC ((\Delta u, \Delta v)) pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P_1)</td>
<td>337,434</td>
<td>106,468</td>
<td>106,468</td>
<td>0,0</td>
<td>105,467</td>
<td>1,1</td>
<td>108,466</td>
</tr>
<tr>
<td>(P_2)</td>
<td>871,650</td>
<td>645,686</td>
<td>643,886</td>
<td>2,0</td>
<td>646,686</td>
<td>1,0</td>
<td>645,685</td>
</tr>
<tr>
<td>(P_3)</td>
<td>579,281</td>
<td>375,315</td>
<td>375,314</td>
<td>0,0</td>
<td>375,314</td>
<td>0,1</td>
<td>376,315</td>
</tr>
<tr>
<td>(P_4)</td>
<td>1124,505</td>
<td>872,545</td>
<td>872,544</td>
<td>0,1</td>
<td>872,545</td>
<td>0,0</td>
<td>877,546</td>
</tr>
</tbody>
</table>

**Table 10: Image matching pixel error for case study 2**

<table>
<thead>
<tr>
<th>Reference ((u,v)) pixel</th>
<th>Actual match ((u,v)) pixel</th>
<th>Calculated Match (H) proposed method ((u,v)) pixel</th>
<th>Match Error proposed ((\Delta u, \Delta v)) pixel</th>
<th>Calculated Match NCC ((u,v)) pixel</th>
<th>Match Error NCC ((\Delta u, \Delta v)) pixel</th>
<th>Calculated Match (H) estimated with RANSAC ((u,v)) pixel</th>
<th>Match Error RANSAC ((\Delta u, \Delta v)) pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P_1)</td>
<td>347,461</td>
<td>114,497</td>
<td>115,498</td>
<td>1,1</td>
<td>897,511</td>
<td>783,14</td>
<td>112,497</td>
</tr>
<tr>
<td>(P_2)</td>
<td>735,557</td>
<td>520,596</td>
<td>522,597</td>
<td>2,1</td>
<td>522,597</td>
<td>2,1</td>
<td>520,597</td>
</tr>
<tr>
<td>(P_3)</td>
<td>1140,452</td>
<td>893,497</td>
<td>891,497</td>
<td>2,0</td>
<td>890,496</td>
<td>3,0</td>
<td>893,495</td>
</tr>
</tbody>
</table>

173
4. Results

Table 11: Image matching pixel error for case study 3

<table>
<thead>
<tr>
<th>Reference ((u,v)) pixel</th>
<th>Actual match ((u,v)) pixel</th>
<th>Calculated Match (H) proposed method ((u,v)) pixel</th>
<th>Match Error (\Delta u, \Delta v) pixel</th>
<th>Calculated Match NCC ((u,v)) pixel</th>
<th>Match Error NCC (\Delta u, \Delta v) pixel</th>
<th>Calculated Match (H) estimated with RANSAC ((u,v)) pixel</th>
<th>Match Error RANSAC (\Delta u, \Delta v) pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P_1)</td>
<td>356,498</td>
<td>136,537</td>
<td>0.1</td>
<td>938,548</td>
<td>802.10</td>
<td>139.534</td>
<td>3.4</td>
</tr>
<tr>
<td>(P_2)</td>
<td>950,587</td>
<td>736,623</td>
<td>0.1</td>
<td>731,623</td>
<td>5.0</td>
<td>736,624</td>
<td>0.1</td>
</tr>
<tr>
<td>(P_3)</td>
<td>730,473</td>
<td>533,514</td>
<td>0.1</td>
<td>533,513</td>
<td>0.1</td>
<td>532,513</td>
<td>1.1</td>
</tr>
<tr>
<td>(P_4)</td>
<td>563,409</td>
<td>366,445</td>
<td>0.1</td>
<td>366,446</td>
<td>0.1</td>
<td>367,446</td>
<td>1.1</td>
</tr>
<tr>
<td>(P_5)</td>
<td>1173,494</td>
<td>931,536</td>
<td>1.1</td>
<td>931,535</td>
<td>0.1</td>
<td>929,537</td>
<td>2.2</td>
</tr>
</tbody>
</table>

As seen Tables 9, 10 and 11 that there is generally a larger mismatch for both the NCC and RANSAC results compared to the proposed method. For NCC, this is because the epipolar line crossed close to both the start and end points for case study 2 and 3 (Figure 4.71), where both points have a region with similar pixel intensity distribution. It is important to note that RANSAC randomly selects matching image points from the entire set of putative matches. This means that an accurate estimate of the homography is not certain if all points within the putative matches are not matched correctly.

![Left view](image1.png) ![Right view](image2.png)

*Figure 4.71: Example of an incorrect match from NCC*

4.3.5 Butt Weld Joint Localisation Results

The 3D position of each test point is calculated in the robot base frame by triangulation using Equations 2.31, 2.34, 2.35 and 3.69. The ground truth data is obtained by using the robot and precision pointer to touch each test point and the
4. Results

position taken from the robot controller. The position error is given by the difference between the ground truth and calculated data. The positioning errors for each case study are shown below in Tables 11, 12 and 13.

Table 11: Localisation error case study 1

<table>
<thead>
<tr>
<th></th>
<th>Proposed $(X_R, Y_R, Z_R)^T$ mm</th>
<th>NCC $(X_R, Y_R, Z_R)^T$ mm</th>
<th>RANSAC $(X_R, Y_R, Z_R)^T$ mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>-0.291 -0.179 0.226</td>
<td>0.134 -0.079 -1.606</td>
<td>-0.661 -0.812 0.832</td>
</tr>
<tr>
<td>$P_2$</td>
<td>-0.056 -0.226 -0.682</td>
<td>0.233 -1.007 2.682</td>
<td>-0.183 -0.792 0.454</td>
</tr>
<tr>
<td>$P_3$</td>
<td>0.162 -0.075 -0.024</td>
<td>0.217 -0.201 -0.501</td>
<td>0.101 -0.081 -0.100</td>
</tr>
<tr>
<td>$P_4$</td>
<td>0.588 0.883 -0.218</td>
<td>0.793 0.856 0.763</td>
<td>2.195 -0.052 6.489</td>
</tr>
</tbody>
</table>

Figure 4.72: Welding results for case study 1 using the proposed method – top view
4. Results

Figure 4.73: Welding results for case study 1 using the proposed method – side view

Table 12: Localisation error case study 2

<table>
<thead>
<tr>
<th></th>
<th>Proposed $(X_R,Y_R,Z_R)^T$ mm</th>
<th>NCC $(X_R,Y_R,Z_R)^T$ mm</th>
<th>RANSAC $(X_R,Y_R,Z_R)^T$ mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>-0.697 0.857 -0.241</td>
<td>-92.766 -42.26 348.15</td>
<td>0.429 1.250 -4.586</td>
</tr>
<tr>
<td>$P_2$</td>
<td>-0.227 -0.221 1.602</td>
<td>-0.229 -0.269 1.627</td>
<td>-0.158 0.099 -0.421</td>
</tr>
<tr>
<td>$P_3$</td>
<td>0.784 0.202 0.424</td>
<td>0.477 0.381 -1.226</td>
<td>1.256 -0.259 2.855</td>
</tr>
</tbody>
</table>
4. Results

Figure 4.74: Welding results for case study 2 using the proposed method – top view

Figure 4.75: Welding results for case study 2 using the proposed method – side view

177
4. Results

Table 13: Localisation error case study 3

<table>
<thead>
<tr>
<th></th>
<th>Proposed $(X_R,Y_R,Z_R)^T$ mm</th>
<th>NCC $(X_R,Y_R,Z_R)^T$ mm</th>
<th>RANSAC $(X_R,Y_R,Z_R)^T$ mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>-0.339</td>
<td>-98.005</td>
<td>-1.311</td>
</tr>
<tr>
<td></td>
<td>-0.722</td>
<td>-43.096</td>
<td>-1.516</td>
</tr>
<tr>
<td></td>
<td>0.258</td>
<td>340.42</td>
<td>2.530</td>
</tr>
<tr>
<td>$P_2$</td>
<td>0.046</td>
<td>-0.285</td>
<td>0.111</td>
</tr>
<tr>
<td></td>
<td>0.111</td>
<td>1.175</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>0.988</td>
<td>-4.972</td>
<td>0.688</td>
</tr>
<tr>
<td>$P_3$</td>
<td>-0.374</td>
<td>-0.386</td>
<td>-0.367</td>
</tr>
<tr>
<td></td>
<td>0.068</td>
<td>0.029</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td>0.901</td>
<td>1.067</td>
<td>-0.489</td>
</tr>
<tr>
<td>$P_4$</td>
<td>-0.053</td>
<td>0.035</td>
<td>-0.241</td>
</tr>
<tr>
<td></td>
<td>0.465</td>
<td>0.453</td>
<td>0.444</td>
</tr>
<tr>
<td></td>
<td>0.315</td>
<td>-0.250</td>
<td>0.250</td>
</tr>
<tr>
<td>$P_5$</td>
<td>0.878</td>
<td>0.671</td>
<td>0.248</td>
</tr>
<tr>
<td></td>
<td>0.991</td>
<td>0.981</td>
<td>1.820</td>
</tr>
<tr>
<td></td>
<td>0.972</td>
<td>0.149</td>
<td>-3.899</td>
</tr>
</tbody>
</table>

Figure 4.76: Welding results for case study 3 using the proposed method – top view
4. Results

![Welding result image](image)

*Figure 4.77: Welding results for case study 3 using the proposed method – side view*

Tables 11, 12 and 13 show that the accuracy for the proposed method is within ±1 mm. Only one point in case study 2 has a $Z_R$ error over 1 mm. All of the $X_R$ and $Y_R$ errors are within the required accuracy. For butt welds, the $X_R$ and $Y_R$ directions can be considered the most important, as they determine the position of the welding wire in the joint. The $Z_R$ direction is the CTWD; small errors of a few millimetres will not greatly affect the quality of the weld as discussed in Section 2.2.5.

The results from the NCC and RANSAC show larger localisation errors compared to the proposed method. The errors from RANSAC can be attributed to the unreliable matching of feature points using cross correlation, which is expected in a welding environment. It can be seen by Figures 4.68, 4.69 and 4.70 that even with several hundred detected feature points in both left and right views, that it is still difficult to obtain matches with a high degree of certainty. This is due to the textureless nature of the feature points. The results for NCC using the epipolar line are worse than RANSAC for this particular application. In Figure 4.71 the epipolar
4. Results

line intersects the weld joint in several locations which have similar pixel intensity distributions to the reference point. This results in large errors as seen above.

It is typically accepted in industry that the position of the wire tip must be within at least the diameter of the electrode. Also for robotic welding applications, it is important to ensure reliable and accurate localisation of the weld joint as positional errors can cause damage to machinery or lead to poor quality welds.

The welds for all three butt weld case studies were completed using Lincoln Electric’s GMAW Pulse waveform[47] with a CTWD of 18mm and 0.9mm diameter welding wire. The wire feed speed, voltage and travel speeds for each case study were set manually based on recommended settings by the manufacturer. The robot path was entered manually into the robot controller using the calculated co-ordinates obtained from the proposed localisation method. The welding results are shown to demonstrate the accuracy of the weld joint detection and localisation method, welding characteristics such as penetration and bead shape are not considered in this thesis as outline in Chapter 3.

The Pulse waveform was chosen as it utilises an adaptive control loop which stabilises the welding arc for variations in CTWD producing high quality, low spatter welds. Alternatively, another of Lincoln Electric’s adaptive waveforms such as RapidArc[48] or PowerMode[49] could also have been used. However, versions of the Pulse waveform have been developed by most welding machine manufacturers. By using the Pulse waveform, it demonstrates that the quality of the welds using the proposed method is not limited to a particular welding power source set-up. The results for all three case studies clearly demonstrate that the proposed planar butt weld detection and localisation method is capable of achieving the required accuracy to achieve effective welds.

Although the adaptive controls in the welding power source can stabilise the welding arc for slight variations in CTWD, it is still very important to ensure that the correct CTWD is maintained as much as possible. As shown in Figure 4.78, if the CTWD (shown as electrical stick out) is too short or too long it will result in a
4. Results

defective weld. Therefore as shown by the localisation results and subsequent welding results, the proposed method provides the accuracy required to achieve high quality welds for robotic arc welding.

The accuracy of the proposed method is achieved by two factors. 1) The accurate matching of image feature points between the left and right views and 2) ensuring a good calibration of the robot and stereo vision system which this thesis proposed. The proper calibration of the robot and vision system enables an accurate calculation of the 3D Cartesian position of the image feature point. The experiment was repeated many times on various shaped welding joints; however the 3 case studies shown in this thesis are effective examples to demonstrate the results of proposed algorithm.

![Gas Metal Arc Welding](image)

*Figure 4.78: The effects of welding variables on weld quality [57]*
4. Results

4.4 Combined Butt and Fillet Weld Joint Detection and Localisation Results

4.4.1 Work Piece Case Studies

To demonstrate the effectiveness of the combined fillet and butt weld joint detection method, it is bench marked with six case studies as presented below. Six industrial style fillet joint configurations were chosen to show the effectiveness of the proposed method to identify weld joints for different base materials and surface finishes. Case study 1 as shown in Figure 4.79 is made from aluminium arranged in typical fillet joint. Case study 2 is a mild steel “tee” fillet joint which is shown in Figure 4.80. In figure 4.81, the work pieces in case study 3 consists of painted steel square hollow section and steel parallel flange channel. Case study 4 shown in Figure 4.82 is curved fillet joint with mild steel work pieces and case study 5 in Figure 4.83 is a fillet joint made from two painted steel square hollow sections. Case study 6 shown in Figure 4.84 is a mild steel butt weld with the same seam line shape as case study 1 in Figure 4.21 in Section 4.3. It is shown again here to compare the accuracy of the adaptive line growing algorithm against the edge detection method introduced in Section 3.2.

The work pieces are placed in arbitrary position on the work bench. The weld joint is identified in both the left and right image using the method introduced in Section 3.4. The test points for confirmation of the localisation accuracy include the start, end and intermediate waypoints required for robot path planning. The 3D Cartesian co-ordinates of the start, end and intermediate waypoints are then calculated using the image matching process described in Section 3.5.
4. Results

Figure 4.79: Aluminium fillet joint - case study 1

Figure 4.80: Mild steel tee fillet joint - case study 2
4. Results

Figure 4.81: Mild steel channel to painted mild steel hollow section - case study 3

Figure 4.82: Mild steel fillet joint – case study 4
4. Results

![Painted mild steel hollow section - case study 5](image1)

Left view  
Right view  

*Figure 4.83: Painted mild steel hollow section - case study 5*

![Mild steel flat plate - case study 6](image2)

Left view  
Right view  

*Figure 4.84: Mild steel flat plate - case study 6*

### 4.4.2 Fillet and Butt Weld Joint Detection Results

The pixel proximity threshold from Equation 3.81 is set to \( T_p = 3 \), the minimum scratch/noise threshold from Equation 3.87 \( T_{L_{min}} = 3 \)mm and the minimum joint length \( T_{L_{max}} = 15 \)mm. These values are not selected empirically, but are determined by the geometrical attributes of the work piece. The proximity threshold \( T_p \) is valid for fillet welds where the joint gap is less than 2 mm. If the gap is larger than 2mm, then the proximity threshold must be made larger. For the scratch/noise threshold, it
is obvious that the weld joint is greater than 3mm and edges line segments less than this can be classified as scratches or edges induced by noise. Secondly the weld joint is also assumed to be greater than 15mm, so any edges equal to or greater than this can be considered to be the weld joint.

The images below display the results of significant stages in the detection of the weld joints starting at initial seed detection and final seed placement. The detected weld seam line is shown superimposed on the weld joint by yellow lines.

4.4.2.1 Case Study 1 – Aluminium fillet joint

Case study 1 is a typical fillet joint using two heavily scratched aluminium plates. The results are shown in the major steps as given by the detection algorithm in Section 3.4. The initial seed locations are shown in Figure 4.85. Due to the heavy scratching, reflections from lighting and other surface imperfections that many initial seeds were identified. However, as explained in Section 3.4, the false seeds are removed and the final seed location is then identified in Figure 4.86 and the final seam line is shown in Figure 4.87. To demonstrate just how accurate the proposed weld joint detection method is, close ups of the weld start and weld end points are shown in Figures 4.88 and 4.89 which show that the seam line has grown in the centre of the weld joint.

![Left View and Right View](image_url)

*Figure 4.85: Initial seeds for the left and right view - case study 1*
4. Results

Figure 4.86: Final seeds for the left and right view - case study 1

Figure 4.87: Final seam line for the left and right view - case study 1
4. Results

Figure 4.88: Close up of start and end points in the left view - case study 1

Figure 4.89: Close up of start and end points in the right view - case study 1

4.4.2.2 Case Study 2 – Mild steel tee fillet joint

Case study 2 demonstrates a so-called “tee” fillet joint. Unlike the methods shown in existing literature, the ends of the weld joint do not terminate at the corners of two plates. The weld joint ends in middle of the base plate, therefore existing methods based on corner pairs such as [52] will not identify where the weld joint starts and stops. However, as can be seen by the results in Figure 4.93 and 4.94, the adaptive line growing method has accurately identified the start and end points. In industry,
4. Results

this kind of weld joint is common. The weld joint is not always configured so that the starts and ends on the corners of two plates as is the case with butt welds. Therefore the proposed adaptive line growing method of weld joint detection is versatile enough to be used for any configuration of fillet joint.

![Initial seeds for the left and right view - case study 2](image1)

*Figure 4.90: Initial seeds for the left and right view - case study 2*

![Initial seeds for the left and right view - case study 2](image2)

*Figure 4.91: Initial seeds for the left and right view - case study 2*
4. Results

Figure 4.92: Final seam line for the left and right view - case study 2

Figure 4.93: Close up of start and end points in the left view - case study 2
4. Results

4.4.2.3 Case Study 3 – Mild steel channel to painted mild steel hollow section

Case study 3 is made from painted steel square hollow section and steel parallel flange channel. Both components have varying degrees of scratching and the flange channel is covered in mill scale and rust. In industry it is typical to find work pieces that are made of painted and unpainted components. In terms of autonomous weld joint detection using computer vision this presents a challenge as the contrast and reflections in the image will varying depending on the colour of the paint. However, the adaptive line growing is capable of identifying the weld joint regardless of different surface coatings as long as the weld joint contains darker pixels. Similar to case study 1, many initial seeds are detected due to scratches, rust and other surface imperfections as shown in Figure 4.95. The final seam line is shown in Figure 4.97 and close ups shown in Figure 4.98 and 4.99 demonstrate just how accurate the proposed method is. As can be seen by these images, the seam line is exactly in the centre of the weld joint.
4. Results

Figure 4.95: Initial seeds for the left and right view - case study 3

Figure 4.96: Final seeds for the left and right view - case study 3
4. Results

Figure 4.97: Final seam line for the left and right view - case study 3

Weld start point
Weld end point

Figure 4.98: Close up of start and end points in the left view - case study 3
4. Results

4.4.2.4 Case Study 4 – Mild steel fillet joint

Case study 4 is a free form curved fillet joint made from two steel plates. Both plates are covered in mill scale; vary degrees of scratching and some surface rust. Just as with the previous case studies, the initial seeds are shown in Figure 4.100 with the final seed locations identified in Figure 4.101. The final seam line close ups in Figures 4.103 and 4.104 once again demonstrate the accuracy of the proposed method with the seam line grown exactly in the centre of the weld joint.
4. Results

Figure 4.101: Final seeds for the left and right view - case study 4

Figure 4.102: Final seam line for the left and right view - case study 4
4. Results

Weld start point

Weld end point

Figure 4.103: Close up of start and end points in the left view - case study 4

Weld start point

Weld end point

Figure 4.104: Close up of start and end points in the right view - case study 4
4. Results

4.4.2.5 Case Study 5 – Painted mild steel hollow section

Case study 5 utilises two painted steel square hollow sections. As can be seen, due to the dark blue paint, therefore is not a sharp pixel intensity change between the weld joint and the two components of the work piece due to the dark colour of the paint and the shadow. In this scenario gradient based edge detection may not be reliable therefore existing methods based on edge detection may not work for this scenario. However the weld joint still contains darker pixels which therefore allow the adaptive line growing to be effective as shown in the results below.

![Initial seeds for the left and right view - case study 5](image1)

**Figure 4.105: Initial seeds for the left and right view - case study 5**

![Final seeds for the left and right view - case study 5](image2)

**Figure 4.106: Final seeds for the left and right view - case study 5**
4. Results

Figure 4.107: Final seam line for the left and right view - case study 5

Weld start point  Weld end point

Figure 4.108: Close up of start and end points in the left view - case study 5
4. Results

![Weld start point and end point](image)

*Figure 4.109: Close up of start and end points in the right view - case study 5*

4.4.2.6 Case Study 6 – Mild steel flat plate

Case study 6 is planar butt weld, with a saw tooth weld joint similar to case study 1 in Section 4.3. It is shown again here to demonstrate that the proposed method is capable of identifying butt welds. As can be seen by the close ups in Figures 4.113 to 4.116, the adaptive line growing has grown in the centre of the joint.

![Initial seeds for the left and right view](image)

*Figure 4.110: Initial seeds for the left and right view - case study 6*
4. Results

Figure 4.111: Final seeds for the left and right view - case study 6

Figure 4.112: Final seam line for the left and right view - case study 6
4. Results

Figure 4.113: Close up of start and end points in the left view - case study 6

Figure 4.114: Close up of intermediate points in the left view - case study 6
4. Results

4.4.2.7 Discussion

The results show that accurate weld joint detection has been achieved for all case studies. They also demonstrate the proposed weld joint detection methods ability to work regardless of base material, joint geometry or surface condition of the work piece.

All case studies contain work pieces with surface imperfections such as scratches, rust and mill scale which is typical of work pieces found in industry. In general the placement and degree of scratching and rust on the surface of the work pieces is
random from work piece to work piece. Therefore the removal of these imperfections using the geometry based methods proposed in this thesis is more robust and intuitive than using pixel area based thresholds in current literature which are typically set by empirical experimentation.

In industry; work pieces can contain materials with different surface finishes and coatings. In case study 3, one of the components is painted while the other is uncoated and in case study 5 both components are painted. The results of case studies 3 and 5 show that the proposed method is capable of detecting weld joints regardless of the surface coatings such as paint which demonstrates the effectiveness of the proposed method for industrial applications.

In this thesis, a single set of geometrically based thresholds are suitable for all case studies shown. Furthermore as can be seen by the results, these thresholds are robust to lighting and reflection changes which can be seen between the left and right stereo views.

4.4.3 Fillet and Butt Weld Joint Image Matching Results

4.4.3.1 Test points

The start, end and intermediate way points are shown below by the yellow “X” markers along with the weld seam line for the left view which is used as the reference.
4. Results

Figure 4.117: Localisation test markers - case study 1

Figure 4.118: Localisation test markers - case study 2
4. Results

Figure 4.119: Localisation test markers - case study 3

Figure 4.120: Localisation test markers - case study 4
4. Results

Figure 4.121: Localisation test markers - case study 5

Figure 4.122: Localisation test markers - case study 6
4. Results

4.4.3.2 Image Matching Results

The reference points in the left image are given by start and end of the seam line, with the intermediate points spaced 20 pixels apart on the left seam line. The intersection radius in Equation 3.92 is set to 1.5 pixels. The maximum height change \( Z_{\text{match-1}} \) between the reference pixels in Equation 3.95 is set to 100mm. The depth of the table \( Z_{\text{table}} \) is calculated by using the robot to touch the table with the precision pointer and recording the value from the robot controller.

Case Study 1

“Reference” refers to the pixel location of the point in the left image to be matched in the right image; “calculated match” is the calculated matching pixel location of the point in the right image. “Actual” is the ground truth pixel location of the matching point in the right image and “Match Error” is the absolute difference between the calculated and the actual matching points in pixels.

\[
\begin{array}{|c|c|c|c|}
\hline
\text{Reference} & \text{Actual match} & \text{Calculated Match} & \text{Match Error} \\
(u,v) \text{ pixel} & (u,v) \text{ pixel} & (u,v) \text{ pixel} & (\Delta u, \Delta v) \text{ pixel} \\
\hline
P_1 & 119,584 & 245,636 & 245,636 & 0,0 \\
\hline
P_2 & 916,367 & 1053,426 & 1053,426 & 0,0 \\
\hline
\end{array}
\]

The reference pixel in the left image and the matching seam line point in the right image for the 2 test points for case study 1 are shown below in Figures 4.123 and 4.124. The red line in the right image is the epipolar line generated by the reference pixel. The blue dots are the seam line points within the intersection radius and the red cross is the matched seam line point.
4. Results

Figure 4.123: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 1

Figure 4.124: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 1

Case Study 2

Table 15: Matching error for case study 2

<table>
<thead>
<tr>
<th></th>
<th>Reference $(u,v)$ pixel</th>
<th>Actual match $(u,v)$ pixel</th>
<th>Calculated Match $(u,v)$ pixel</th>
<th>Match Error proposed $(\Delta u, \Delta v)$ pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>385,513</td>
<td>516,559</td>
<td>515,558</td>
<td>1,1</td>
</tr>
<tr>
<td>$P_2$</td>
<td>755,391</td>
<td>898,443</td>
<td>900,442</td>
<td>2,1</td>
</tr>
</tbody>
</table>
4. Results

Figure 4.125: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 2

Figure 4.126: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 2

Case Study 3

Table 16: Matching error for case study 3

<table>
<thead>
<tr>
<th>Reference (u,v) pixel</th>
<th>Actual match (u,v) pixel</th>
<th>Calculated Match (u, v) pixel</th>
<th>Match Error proposed (Δu, Δv) pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>118,573</td>
<td>153,623</td>
<td>2.1</td>
</tr>
<tr>
<td>$P_2$</td>
<td>1087,335</td>
<td>1180,400</td>
<td>0.0</td>
</tr>
</tbody>
</table>
4. Results

![Left view](image1) ![Right view](image2)

*Figure 4.127: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 3*

![Left view](image3) ![Right view](image4)

*Figure 4.128: Reference pixel in the left image and the matching pixel in the right image for test point 2 – case study 3*

**Case Study 4**

**Table 17: Matching error for case study 4**

<table>
<thead>
<tr>
<th></th>
<th>Reference ((u,v)) pixel</th>
<th>Actual match ((u,v))pixel</th>
<th>Calculated Match ((u,v)) pixel</th>
<th>Match Error proposed ((\Delta u, \Delta v)) pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P_1)</td>
<td>120,754</td>
<td>237,824</td>
<td>240,825</td>
<td>3.1</td>
</tr>
<tr>
<td>(P_2)</td>
<td>360,590</td>
<td>509,613</td>
<td>509,613</td>
<td>0.0</td>
</tr>
<tr>
<td>(P_3)</td>
<td>720,434</td>
<td>855,483</td>
<td>856,483</td>
<td>1.0</td>
</tr>
<tr>
<td>(P_4)</td>
<td>1055,404</td>
<td>1225,646</td>
<td>1225,646</td>
<td>0.0</td>
</tr>
</tbody>
</table>
4. Results

Figure 4.129: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 4

Figure 4.130: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 4
4. Results

*Figure 4.131: Reference pixel (left image) and the matching pixel (right image) for test point 3 – case study 3*

*Figure 4.132: Reference pixel (left image) and the matching pixel (right image) for test point 4 – case study 4*

**Case Study 5**

*Table 18: Matching error for case study 5*

<table>
<thead>
<tr>
<th></th>
<th>Reference $(u,v)$ pixel</th>
<th>Actual match $(u,v)$ pixel</th>
<th>Calculated Match $(u, v)$ pixel</th>
<th>Match Error proposed $(\Delta u, \Delta v)$ pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>112,633</td>
<td>113,690</td>
<td>114,690</td>
<td>1.0</td>
</tr>
<tr>
<td>$P_2$</td>
<td>1066,505</td>
<td>1082,550</td>
<td>1080,550</td>
<td>2.0</td>
</tr>
</tbody>
</table>
4. Results

![Left view](image1.png) ![Right view](image2.png)

Figure 4.133: Reference pixel (left image) and the matching pixel (right image) for test point 1 – case study 5

![Left view](image3.png) ![Right view](image4.png)

Figure 4.134: Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 5

Case Study 6

<table>
<thead>
<tr>
<th></th>
<th>Reference ((u,v)) pixel</th>
<th>Actual match ((u,v)) pixel</th>
<th>Calculated Match ((u,v)) pixel</th>
<th>Match Error proposed ((\Delta u, \Delta v)) pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P_1)</td>
<td>299,465</td>
<td>83,502</td>
<td>83,501</td>
<td>0,1</td>
</tr>
<tr>
<td>(P_2)</td>
<td>520,295</td>
<td>338,328</td>
<td>338,328</td>
<td>0,0</td>
</tr>
<tr>
<td>(P_3)</td>
<td>848,638</td>
<td>644,676</td>
<td>647,675</td>
<td>3,1</td>
</tr>
<tr>
<td>(P_4)</td>
<td>1091,472</td>
<td>870,516</td>
<td>869,517</td>
<td>1,1</td>
</tr>
</tbody>
</table>
4. Results

*Figure 4.135:* Reference pixel (left image) and the matching pixel (right image) for test point 1 showing multiple intersections – case study 6

*Figure 4.136:* Reference pixel (left image) and the matching pixel (right image) for test point 2 – case study 6
4. Results

Figure 4.17: Reference pixel (left image) and the matching pixel (right image) for test point 3 – case study 6

Figure 4.18: Reference pixel (left image) and the matching pixel (right image) for test point 4 – case study 6

4.4.4 Fillet and Butt Weld Joint Localisation Results

The 3D position of each test point for the 6 case studies is calculated in the robot base frame using Equations 2.31, 2.34, 2.35 and 3.69. The ground truth data is obtained by using the robot and precision pointer to touch each test point and record its position is recorded from the robot controller. The position error is given by the
difference between the two. The localisation errors for each case study are shown in the tables below.

The welded work pieces for case studies 2,3,4,5 and 6 are shown below in Figures 4.139 to 4.148. As the welding equipment used in this thesis in only setup for welding steel, the welded results for case study 1 are not shown, although it can still be seen that the proposed method is capable of accurately detecting and locating weld joints for aluminium as well as steel. The welds were completed using a GMAW Pulse waveform[47] with a CTWD of 18mm and 0.9mm diameter welding wire. The wire feed speed, voltage and travel speeds for each case study were set manually based on recommended settings by the manufacturer. The robot path was entered manually into the robot controller using the calculated co-ordinates obtained from the proposed localisation method. The welding results are shown to demonstrate the accuracy of the weld joint detection and localisation method, welding characteristics such as penetration and bead shape are not considered in this thesis as outline in Chapter 3.

Similar to the welding results for the planar butt welds in Section 4.3.5, the Pulse waveform was chosen as it has an adaptive control loop which stabilises the welding output for variations in CTWD producing high quality, low spatter welds. Although the Lincoln Electric Pulse waveform is used in this thesis, variations of the Pulse waveform is available on most advanced welding power sources. Therefore the results obtained in this thesis are not dependent a particular welding power source set-up.

*Table 20: Localisation error for case study 1*

<table>
<thead>
<tr>
<th></th>
<th>Error $X_R$ $mm$</th>
<th>Error $Y_R$ $mm$</th>
<th>Error $Z_R$ $mm$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>-0.27</td>
<td>-0.77</td>
<td>-0.39</td>
</tr>
<tr>
<td>$P_2$</td>
<td>-0.59</td>
<td>0.04</td>
<td>-0.78</td>
</tr>
</tbody>
</table>
4. Results

**Table 21: Localisation error for case study 2**

<table>
<thead>
<tr>
<th></th>
<th>Error $X_R$ $\text{mm}$</th>
<th>Error $Y_R$ $\text{mm}$</th>
<th>Error $Z_R$ $\text{mm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>0.55</td>
<td>0.93</td>
<td>0.41</td>
</tr>
<tr>
<td>$P_2$</td>
<td>-0.50</td>
<td>0.14</td>
<td>-0.37</td>
</tr>
</tbody>
</table>

**Table 22: Localisation error for case study 3**

<table>
<thead>
<tr>
<th></th>
<th>Error $X_R$ $\text{mm}$</th>
<th>Error $Y_R$ $\text{mm}$</th>
<th>Error $Z_R$ $\text{mm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>-1.02</td>
<td>0.93</td>
<td>0.18</td>
</tr>
<tr>
<td>$P_2$</td>
<td>0.24</td>
<td>0.82</td>
<td>0.88</td>
</tr>
</tbody>
</table>

**Table 23: Localisation error for case study 4**

<table>
<thead>
<tr>
<th></th>
<th>Error $X_R$ $\text{mm}$</th>
<th>Error $Y_R$ $\text{mm}$</th>
<th>Error $Z_R$ $\text{mm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>0.35</td>
<td>-0.64</td>
<td>0.99</td>
</tr>
<tr>
<td>$P_2$</td>
<td>0.93</td>
<td>0.38</td>
<td>-0.17</td>
</tr>
<tr>
<td>$P_3$</td>
<td>-0.04</td>
<td>-0.97</td>
<td>-0.74</td>
</tr>
<tr>
<td>$P_4$</td>
<td>-0.62</td>
<td>0.94</td>
<td>-0.46</td>
</tr>
</tbody>
</table>

**Table 24: Localisation error for case study 5**

<table>
<thead>
<tr>
<th></th>
<th>Error $X_R$ $\text{mm}$</th>
<th>Error $Y_R$ $\text{mm}$</th>
<th>Error $Z_R$ $\text{mm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>-0.30</td>
<td>0.39</td>
<td>0.12</td>
</tr>
<tr>
<td>$P_2$</td>
<td>-0.70</td>
<td>0.63</td>
<td>-0.34</td>
</tr>
</tbody>
</table>

**Table 25: Localisation error for case study 6**

<table>
<thead>
<tr>
<th></th>
<th>Error $X_R$ $\text{mm}$</th>
<th>Error $Y_R$ $\text{mm}$</th>
<th>Error $Z_R$ $\text{mm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>0.25</td>
<td>-0.54</td>
<td>0.40</td>
</tr>
<tr>
<td>$P_2$</td>
<td>0.73</td>
<td>-0.43</td>
<td>-0.49</td>
</tr>
<tr>
<td>$P_3$</td>
<td>-0.63</td>
<td>-1.06</td>
<td>4.31</td>
</tr>
<tr>
<td>$P_4$</td>
<td>0.88</td>
<td>0.43</td>
<td>0.91</td>
</tr>
</tbody>
</table>
4. Results

Figure 4.139: Welding results for case study 2 using the proposed method – front view

Figure 4.140: Welding results for case study 2 using the proposed method – side view
4. Results

Figure 4.141: Welding results for case study 3 using the proposed method – front view

Figure 4.142: Welding results for case study 3 using the proposed method – side view
4. Results

Figure 4.143: Welding results for case study 4 using the proposed method – front view

Figure 4.144: Welding results for case study 4 using the proposed method – close up
4. Results

Figure 4.145: Welding results for case study 5 using the proposed method – front view

Figure 4.146: Welding results for case study 5 using the proposed method – side view
4. Results

Figure 4.14: Welding results for case study 6 using the proposed method – top view

Figure 4.148: Welding results for case study 6 using the proposed method – side view
4. Results

![Top view and Side view images of welds](image)

*Figure 4.149: Close up of the “test point 2” weld using the proposed method – case study 6*

![Top view and Side view images of welds](image)

*Figure 4.150: Close up of the “test point 3” weld using the proposed method – case study 6*

The results in Tables 20 - 25 show the majority of test points are within approximately ±1mm. Only a few points have an error larger than 1mm, however considering that the repeatability of the robot is ±0.08mm, an error of 1.02mm in $X_R$ for case study 3 and 1.06mm for $Y_R$ in case study 6 can be considered to be approximately 1mm as 0.02mm and 0.06mm are less than the repeatability of the robot.
4. Results

The welding results for case studies 2, 3, 4, 5 and 6 shows that the proposed butt and fillet weld joint detection and localisation method has achieved the required accuracy to produce welds that are positioned within the joint, fusing the two components of the work piece, resulting in welds that are acceptable both visually and structurally.

Figure 4.137 demonstrates a worst case scenario where a matching error has resulting in the $Z_R$ direction error for case study 6 is greater than 1mm which affects the CTWD. However the $X_R$ and $Y_R$ directions are still broadly within 1mm, which means the wire is still positioned within the weld joint. The typical CTWD for GMAW is 15-19mm which means that an error of 4.31mm will not result in the welding torch crashing into the work piece. As mentioned in Section 2.2.5 the adaptive control loop in modern welding power sources such the Lincoln Electric PowerWave can handle some fluctuation in CTWD within its operating range without affecting the quality of the weld [47]. Therefore even with in this worst case scenario, the proposed method is still reliable enough to avoid damage to machinery and provide adequate welding quality as shown by the welded results for case study 6 in Figure 4.147 and 4.148. As can be seen in the close up images of test points 2 and 3 in Figures 4.149 and 4.150 respectively, there is no noticeable effect of the variation in CTWD from test point 2 to test point 3.
5. Conclusions

Chapter 5  Conclusions

5.1 Conclusions

At present, industrial welding robots are programmed through “teach and playback” methods by human operators. It can take a significant amount of time and expense to program paths for each new work piece. This setup time can be justified in mass production, however for low to medium volume manufacturing or even repair and maintenance work it is often quicker and more convenient to weld the parts manually. To bring the benefits of robotic welding to these industries, it must become more flexible.

The contribution of this thesis is the development of computer vision methods for autonomous weld joint detection and localisation which can be used for vision guided robotic arc welding. The weld joint detection and localisation methods are capable of automatically detecting the weld joint and then providing the 3D co-ordinates of the weld joint to the robot controller for path planning. To meet the requirements for industrial implementation, the computer vision methods are robust to overcome the environmental and operational difficulties of the welding environment. These include reflections from lighting, imperfections on the work piece such as paint, rust, mill scale and scratches which is not consistent between work pieces. Operationally the system is capable of implementation in an industrial setting. With this in mind, the developed system is practical and quick to calibrate.

In this thesis, a robot mounted eye-in-hand stereo vision system was used to detect the weld joint and to calculate its 3D real world position for robot path planning. An automatic calibration method was developed to calibrate the robot arm and the robot mounted cameras simultaneously without the use of additional sensors such as external 3D measurement devices and laser scanners. The calibration is carried out using only the robot mounted cameras and a specially designed calibrated board. Non-linear optimisation is used to minimise the absolute positioning errors between the robot and the world reference frame.
5. Conclusions

The results show that the proposed automatic calibration algorithm reduces the time required to calibrate the cameras by 62% compared with the manual point and click method [14]. In addition to speed, the results have shown that this method is capable of achieving the required accuracy of ±1 mm without the use of expensive external measurement devices. Although the camera calibration is an off-line process, the algorithm presented in this thesis is particularly useful in a production environment as it reduces the system down time and requires no special skills of the operator.

Two weld joint detection methods were developed, which enable the automatic identification of weld joints in realistic configurations for multiple base materials without prior knowledge of the shape or location of weld joint in the image.

The first weld joint detection method introduced an algorithm specifically for planar butt welds. The algorithm segments the work piece from the background without the use of a pre-defined ROI, leading to the reliable detection of narrow weld joints where the edges of the work piece are pressed against each other for ferrous materials such as mild steel. Once the background is segmented a set of algorithms is used to identify the weld joint. For planar butt weld joint localisation, a 2D homography transformation was adopted. The advantage of the homography transformation method is that it does not rely on either epipolar geometry or pixel intensities for image matching. However, the calculation of the homography matrix requires the calculation of at least four corresponding points in the two images which are on the same plane as the weld joint. The geometry of the work piece itself is used to provide these corresponding points by using the four outside corners of the work piece. The four outside corners are provided during the background subtraction of the weld joint identification process.

The experimental results show that the proposed planar butt weld joint method is able to identify weld joints of various shapes. The advantage of this method is that the joint can be identified without prior knowledge of the geometry or location of the joint from a single image. Furthermore it is shown to work well even in the presence of imperfections on the surface of the steel such as scratches and mill scale. The
5. Conclusions

Experimental results also show that this method is an effective alternative to the joint identification algorithms available in the literature, especially for ferrous materials in low contrast images.

The homography-based image matching process allows for more reliable image matching regardless of image contrast and lighting conditions. The results are compared with two established methods. The results show that the proposed matching homography estimation technique is more reliable than NCC as it is not affected by local pixel intensities. It is also difficult to estimate the homography transformation using RANSAC as establishing a sufficient number of correct matches is difficult in a welding environment. However, the accuracy of the homography transformation is reliant on the accuracy of the corner detection calculation. Furthermore, the homography-based image matching method is intended for weld joints on a single plane.

The second weld joint detection algorithm introduced a novel approach for the identification of both fillet and butt welds using a new adaptive line growing algorithm. Currently, there are not mature methods for the detection of fillet joints. The proposed method is capable of identifying the joint in the global image without the use of a ROI or prior knowledge of the weld joint geometry, shape or base material. Seeds are placed on edges that are likely to be the weld joint. Each seed is then locally assessed for its likelihood to be on the welding joint. Once the correct seed is chosen, an adaptive line growing algorithm is used to spread out and follow the weld joint until the ends of the joint are reached. The adaptive line growing is based on the assumption that the weld joint is darker than the surface of the work pieces either side of the joint.

A distinct advantage in terms of practical applications is that the proposed method provides a single method for the detection of both fillet and butt welds and also it does not rely on the use of thresholds based on pixel area which cannot be applied intuitively by an operator. The thresholds are based on the physical geometry of the weld joint and are measured in millimetres as opposed to pixels. Experimental results on a wide range of base materials and surface finishes which included paint, rust,
5. Conclusions

Heavy scratching and mill scale show the value of the proposed method. It is capable of accurately identifying the weld joint for both fillet and butt weld configurations without altering the setup.

While both of the proposed methods are capable of detecting weld joints for multiple base materials and weld shapes, the planar butt weld detection is limited to work pieces with straight line boundaries due to the background subtraction method. The main limitation of the combined planar and non-planar weld joint detection is the assumption that the weld joint is darker than the surrounding work piece surfaces. While it is safe to assume this in a well-lit environment, there may be circumstances where this is not the case. For example, if the robot is located outdoors, under a sky light, or next to a roller doors where the lighting conditions can change or direct light is shone on the work piece. Shadows from the robot arm and ancillary equipment such as fume extraction arms and jigs can also limit the effectiveness of this method. However, for a robot in a factory, the lighting can be controlled through engineered solutions such as strategically placed light sources.

A second image matching algorithm is also developed for fillet and butt welds. This method uses the intersection of the epipolar line and weld seam line. Geometrical constraints are introduced for situations where the epipolar line and weld seam line intersect in more than one location.

The 3D positions of the weld joints are obtained using matched image points a calibrated eye-in-hand stereo vision system via triangulation. The experimental results show that the proposed algorithms are capable of achieving the required accuracy of ±1mm. This thesis has filled the void that currently exists in weld joint detection and localisation and has introduced computer vision algorithms which are suitable for industrial applications of robotic arc welding as demonstrated by the welding results.
5. Conclusions

5.2 Future Work

While the methods proposed in this thesis provide reliable and robust solutions for weld joint detection and localisation, there is opportunity for future research to build and extend these methods for an even wider range of applications. A few key area for future research include:

1. Develop methods for detection and localisation of weld joints in larger work pieces involving multiple weld joints such as in shipyard and pipeline applications.
2. Increase the robustness of the adaptive line growing method to adapt to varied lighting conditions such as bright spots from reflections and dark spots from shadows.
3. Extend the planar work piece boundary subtraction to include circular shapes.
4. Develop robot path planning methods for autonomous welding of work pieces. The path planning would incorporate welding specific constraints such as correct welding torch posture, welding to minimise distortion and avoiding obstacles such as tooling and jigs.
5. Develop multi-robot welding systems where more than one robot can work in a co-ordinated environment on large work pieces such as in shipyard and automotive applications.
6. Develop an intelligent system capable of recognising the required welding procedures such as voltage, wire feed speed and travel speed. It should also be able to monitor and adapt the weld path online. This would reduce human interaction as the machine would be capable of achieving high quality welds with little expertise required by the operator.

It is envisaged that the methods proposed in this thesis will eventually be developed into a commercial package for Lincoln Electric which can be implemented in industry.
References


