

UNIVERSITY OF TWENTE. 

Optical Laser Projection Profilometry for 3D Reconstruction and Point Cloud Segmentation of Drinking Water Pipeline Interiors

by

Louis Daniël Lizarazo Fuentes

A thesis submitted to the
Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS)
in fulfillment of the requirements for the degree of

MSc in Business Information Technology

Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS)

University of Twente

Enschede, Overijssel, The Netherlands

February 2026

ABSTRACT

The integrity of drinking water pipelines is essential for ensuring public health and conserving increasingly scarce water resources. Internal inspection of pipelines enables non-destructive integrity assessment and informed maintenance decision-making for water infrastructure operators. Laser Projection Profilometry is a cost-effective, high-resolution approach for acquiring geometric information of inner pipeline surfaces.

This work proposes a comprehensive data processing pipeline for Laser Projection Profilometry, which enables 3D reconstruction and defect-oriented segmentation of pipeline interiors using a single-camera sensor configuration. The pipeline consists of camera calibration, image preprocessing, laser line extraction, 3D reconstruction in image coordinates, point cloud preprocessing, and unsupervised clustering-based segmentation. Individual image-sourced point clouds are spatially registered in 3D using estimated laser profile circle centers and stacked in the longitudinal direction. Quantitative evaluation is conducted using quasi-synthetic reference 3D point clouds generated from real measurement inputs, allowing controlled variation of pipeline geometry and defect characteristics while maintaining realistic sensor conditions.

Experimental results obtained from multiple real-world datasets demonstrate that the proposed pipeline achieves mean point-wise registration errors of 1.08–2.08 px, corresponding to 0.43–1.79 mm when converted using dataset-specific pixel-to-millimeter calibrations. The corresponding HD95 values range from 2.50–3.91 px and from 0.99–3.15 mm across datasets. Variations in both error metrics are primarily attributable to differences in pipeline diameter, surface material, and laser emitter intensity across the datasets. The method reliably reconstructs and localizes both positive (material buildup) and negative radius (material loss) defects across varying pipeline geometries under controlled inspection conditions. Density-based clustering (DBSCAN) proved robust and computationally efficient for defect segmentation, exhibiting real-time performance, whereas a hierarchical pruning approach (Torque Clustering) required careful parameterization and incurred a significantly higher computational cost. Identified limitations include material-dependent reflectance effects, geometric reconstruction of negative radius defects, sensitivity to robot orientation, and scalability constraints in hierarchical clustering. Overall, this work demonstrates the suitability of a Laser Projection Profilometry-based data processing pipeline for internal drinking water pipeline inspection and provides a quantitative foundation for future research toward more robust, scalable, and deployable inspection systems.

Keywords: 3D Reconstruction ; Laser Projection Profilometry ; Point Cloud Segmentation ; Non-Destructive In Line Pipeline Inspection

CONTENTS

Abstract	i
List of Abbreviations	iv
1 Introduction	1
1.1 Research Background	2
1.2 Research Motivations and Objectives	4
2 Literature Review	6
2.1 Methodology	6
2.2 Meta analysis	8
2.2.1 Journals	8
2.3 Optical Inspection	9
2.3.1 Methodological Taxonomy	10
2.3.2 Evaluation techniques	11
2.3.3 Sensing Modalities	11
2.4 Gaps in the literature	15
3 Case study Set-Up	16
3.1 Robot	16
3.2 Test setup	17
3.3 Acquired Data	18
3.4 Synthetic Data	18
3.4.1 Synthetic images	19
3.4.2 Synthetic point clouds	19
4 Methodology	21
4.1 Data Mining Methodology for Engineering Applications	21
4.2 Pipeline Overview	23
4.3 Camera Calibration	23
4.4 Image Preprocessing	24
4.4.1 Edge-Preserving Filter	24
4.4.2 Grid-Based Concentric Circle Center Detection	25
4.4.3 Linear Scaled Polar Transform	26

4.4.4	Region of Interest	26
4.5	Laser Extraction	27
4.5.1	Find peaks.	27
4.5.2	Graph Construction	27
4.5.3	1D k-means	28
4.5.4	A* Path finding	28
4.6	Point cloud preprocessing	28
4.6.1	Residual Computation	29
4.6.2	MinMaxScaler.	29
4.7	Segmentation.	29
4.7.1	Density-Based Spatial Clustering of Applications with Noise	30
4.7.2	Torque Clustering.	30
4.8	Evaluation	32
5	Results and Discussion	34
5.1	Calibration	34
5.2	Data	35
5.3	Image Preprocessing	38
5.4	Laser line extraction	38
5.5	Reconstructions	39
5.6	3D Point Cloud Preprocessing.	43
5.7	Segmentation.	44
5.8	Performance	46
6	Conclusion and Discussion	47
6.1	Conclusion	47
6.2	Practical and Scientific Contributions	49
6.3	Limitations	49
6.4	Future Research Recommendations	50
	References	52
A	Appendix A: Literature Review	61

ABBREVIATIONS

AUV	Autonomous Underwater Vehicle.
BCSF	Bidirectional Cloth Simulation Filtering.
CHT	Circular Hough Transform.
CRISP-DM	CRoss Industry Standard Process for Data Mining.
Dataset 1	300-310mm $\varnothing$ PVC; plastic blocks.
Dataset 2	300mm $\varnothing$ PVC; uncoated stainless steel evaluation plate.
Dataset 3	580mm $\varnothing$ PVC; uncoated stainless steel evaluation plate.
Dataset 4	Uncoated metal form with significant ovality.
DBSCAN	Density-Based Spatial Clustering of Applications with Noise.
DMME	Data Mining Methodology for Engineering Applications.
DRG	Density-based Region Growing.
FOV	Field Of View.
FWCI	Field-Weighted Citation Impact.
HD95	Hausdorff Distance 95th Percentile.
ICP	Iterative Closest Point.
ILI	In Line Inspection.
IMU	Inertial Measurement Unit.
LiDAR	Light Detection and Ranging.
LPP	Laser Projection Profilometry.
LRP	Laser Range Profilometry.
MAE	Mean Absolute Error.
PIG	Pipeline Inspection Gauge.
ROI	Region of Interest.
ROV	Remotely Operated Vehicle.
SAM	Segment Anything Model.
SLAM	Simultaneous Localization and Mapping.
TC	Torque Clustering.
TSCL	Torque Sorted Connections List.

1

INTRODUCTION

The integrity of drinking water pipelines is essential for ensuring public health and conserving increasingly scarce water resources. In sewer pipelines in the US alone around 13 thousand pipeline related accidents have resulted in nearly 300 deaths, more than a thousand injuries and estimated economic losses of \$10.83 billion in a span of two decades [1]. Furthermore globally water loss remains an issue with the World Bank [2] estimating that developed countries experience physical losses of around 12% of drinking water during distribution, while developing countries face losses as high as 21%. More recent data in the Netherlands estimated that 6–7% of all treated drinking water is lost as non-revenue water, mostly consisting of physical losses [3]. These losses are not just wasted water and damage caused, but also costs associated with treatment and transportation. Dutch investments in the underground drinking water network have doubled in recent years [3]. Network age and the subsequent phase out of old pipes is a global issue [4], for example in the Dutch network asbestos cement and cast iron is still being replaced as illustrated in Figure 1.1. Thus methods supporting decision making in maintenance for increasing asset lifetime, such as estimating failure risk, become increasingly important [5].

Development of the drinking water network

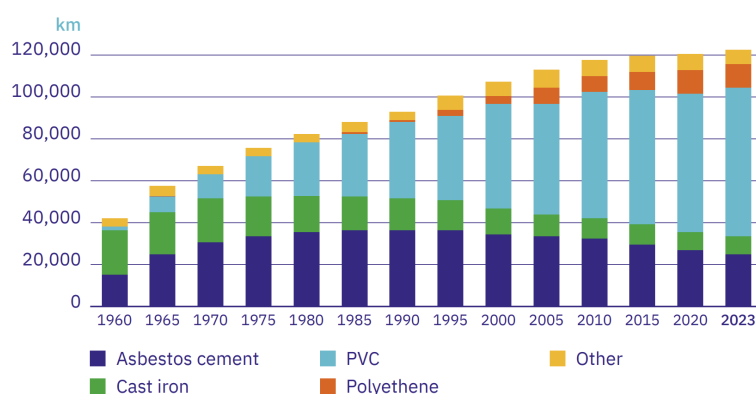


Figure 1.1: Dutch drinking water network size and distribution per material (1960-2023) [3]

Cast iron or steel pipelines generally follow the degradation life cycle described in Figure 1.2 where damage starts to accumulate until a defect (small leaks, cracks, dents, holes, ovality etc.) or even a failure occurs [5]. Inspection of pipelines helps with providing information on the state of the pipeline providing crucial information for the decision making process as illustrated in Figure 1.3 for cost estimation [5, 6]. This supports utility companies in prioritizing repairs, reducing emergency interventions, and extending the lifetime of assets, which leads to better capital allocation and improved service reliability [5–8].

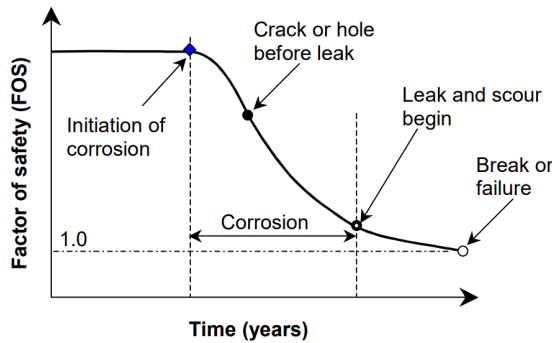


Figure 1.2: Defect types in a pipe's life cycle [5]

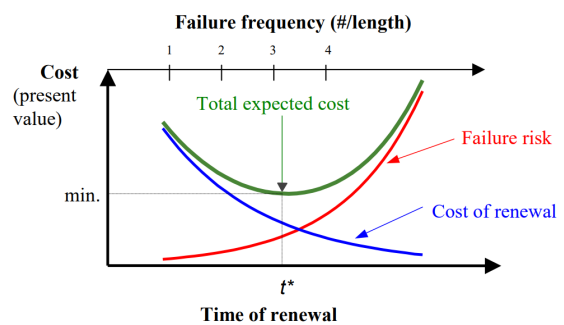


Figure 1.3: Cost based decision making in pipes [5]

1.1. RESEARCH BACKGROUND

Pipeline inspection methods consist of destructive and non-destructive techniques. The latter is preferred due to comparable diagnostic performance and preservation of physical pipeline integrity [6]. Non-destructive inspection relies either on *In Line Inspection (ILI)*, where a sensor-equipped device travels inside the pipeline, or on external inspection performed from above the buried infrastructure [9]. *ILI* methods are preferred as they offer a higher resolution, although their application is limited by geometric or access constraints [9]. Many types of sensors can be integrated into *ILI* systems, including but not limited to optical, piezoelectric bimorph, and magnetic flux leakage sensors [9, 10], see Figure 1.4, Figure 1.5 and Figure 1.6.

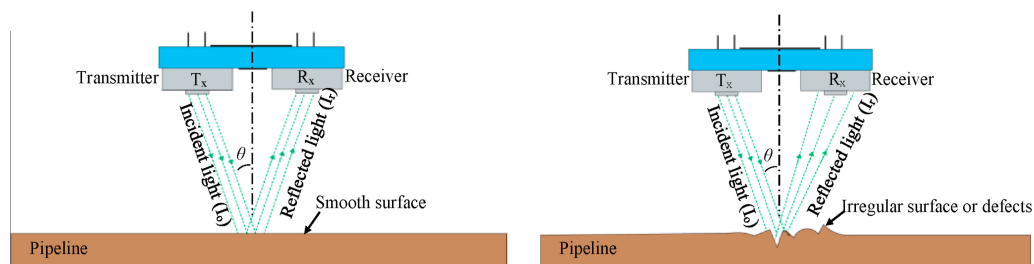


Figure 1.4: Optical sensing utilizes emitted light and its reflection to identify surface-level pipeline defects and structural anomalies[10]

Optical inspection methods are flexible across different pipeline materials. Optical systems consist of a light emitter and a sensor recording the reflection of light from the surface it hits [10]. Light sources include lasers (monochromatic and coherent) and LEDs (incoherent) [11] among others. Laser-based systems can be used for profilometry [12–15, 15–23] where the res-

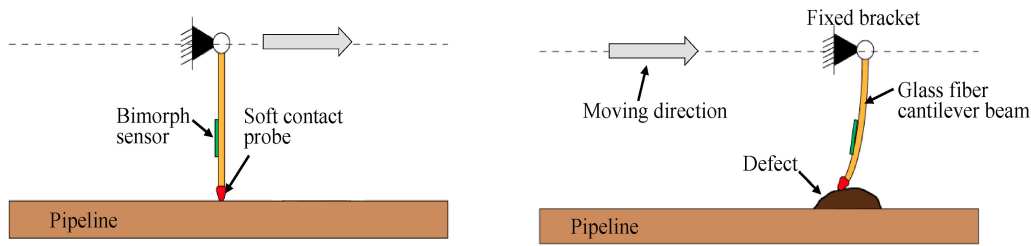


Figure 1.5: Piezoelectric bimorph sensing converts mechanical pipe vibrations and pressure waves into electrical signals for direct defect detection [10]

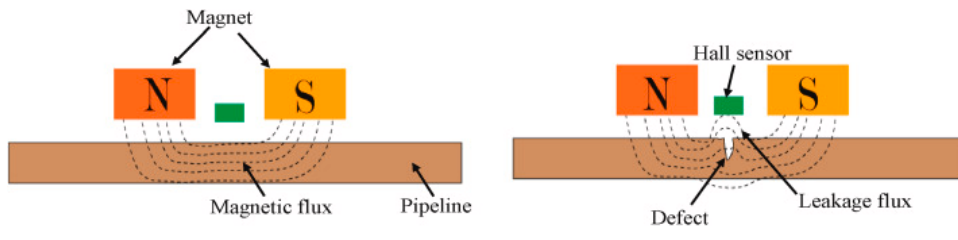


Figure 1.6: Magnetic flux leakage detects material loss and corrosion by measuring magnetic field distortions[10]

olution of laser projections (laser and conical mirror [12, 14, 16–18]) provides an advantage over laser ranging. The laser projection profiles a cross section of the pipe and can be captured using a camera with a sufficient **Field Of View (FOV)** resulting in a 2D point cloud of the profile for each image.

Wide-angle lenses or mirrors with standard lenses [12, 16] are used to achieve a sufficient **FOV**. Lenses introduce radial- and tangential distortion, which affect the spatial accuracy of captured images [24]. The camera's intrinsic and extrinsic parameters (see Figure 1.7) define the projection between 3D world space and the 2D image plane which maps image points to their world coordinates [24] which enables distortion correction of the images.

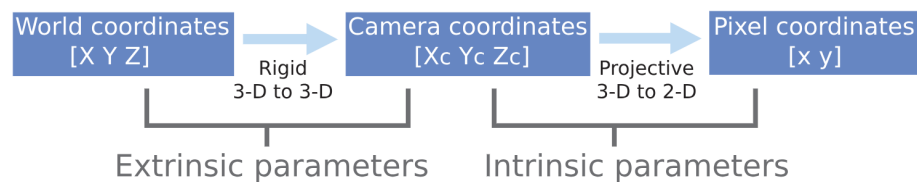


Figure 1.7: Coordinate transformations [25].

The acquired data can be used to create a 3D model of the internal pipeline surface, which provides a quantitative representation of the structure which can be automatically segmented facilitating an automatic quantitative assessment of surface characteristics and defects reducing workload and minimizing human subjective interpretation [26, 27]. Rosenxt is a company dedicated to creating inspection and data analysis technologies that improve decision making for critical infrastructure. By integrating optical data acquisition, distortion correction, reconstruction, and segmentation, Rosenxt can improve their offering in waterline integrity management improving proactive maintenance strategies for their customers.

1.2. RESEARCH MOTIVATIONS AND OBJECTIVES

Many recent papers evaluated laser based systems for non-destructive [ILI](#) as it enables geometric reconstruction of internal surfaces and detection of defects. Those studies have demonstrated the potential of [Laser Projection Profilometry \(LPP\)](#) [12–18], [Laser Range Profilometry \(LRP\)](#) [15, 20–23] and pattern projection [28] in 3D reconstruction. However no studies found in the [Chapter 2](#) evaluated the performance of [LPP](#) sourced point cloud segmentation or were applied in water filled pipelines, where light scattering, refraction, and turbidity can create challenges to measurements. This gap in the literature presents both a scientific and practical motivation for this research: to investigate the feasibility and robustness of [LPP](#) based [ILI](#) and segmentation of the resulting 3D point cloud.

The majority of recent optical [ILI](#) studies [19, 27, 29–50], only one of which uses [LPP](#) [19], have applied deep learning techniques directly to raw image data. Subsequently bypassing the potential benefits of geometric interpretation of reconstructed surfaces. Only two studies [21, 22] found in [Chapter 2](#) processed pipeline point cloud data, both derived from [LRP](#) rather than [LPP](#), and both relied on combinations of [Bidirectional Cloth Simulation Filtering \(BCSF\)](#), [Density-Based Spatial Clustering of Applications with Noise \(DBSCAN\)](#), and [Density-based Region Growing \(DRG\)](#). The segmentation of [LPP](#) sourced point clouds using unsupervised methods remains unexplored. Addressing this gap shifts inspection from appearance-driven classification toward geometry-aware surface understanding, which directly underpins interpretability, robustness, and operational relevance.

From an application standpoint, pipeline operators and evaluators are increasingly seeking automated, data-driven solutions that can perform under diverse environmental conditions and provide interpretable, geometric insights into the internal state of drinking water infrastructure. By combining 3D reconstruction and unsupervised segmentation, the proposed approach could reduce the need for expert manual inspection, improve defect localization accuracy, and support the development of scalable, proactive maintenance workflows. This aligns with the goals of companies such as Rosenxt, which aim to integrate [ILI](#) sensing, data analytics, and infrastructure management into unified inspection platforms.

The primary goal of this study, therefore, is to develop and evaluate a [LPP](#) data processing pipeline capable of camera calibration, 3D reconstruction and unsupervised segmentation of pipeline surfaces. The research explores the entire processing chain, from optical data acquisition and calibration to the generation and segmentation of 3D point clouds. The overarching objective is to assess the feasibility of obtaining accurate geometric information and to establish a segmentation methodology that can autonomously distinguish surface features relevant to pipeline integrity assessment. With the deployment of this pipeline, several advantages can be achieved:

1. Improved defect detection and localization: Quantitative surface geometry enables more precise identification of structural deformations.
2. Reduced reliance on manual interpretation: Automated segmentation minimizes subject-

- tive bias and operator workload, improving reproducibility and scalability of inspections.
3. Enhanced robustness under challenging conditions: By demonstrating performance inside pipelines, the method extends the applicability of optical inspection to real-world operational contexts.
 4. Modularity and data re-usability: The 3D representation allows for fusion with data from other sensing modalities.

Based on these motivations, the study addresses the following research- and sub questions:

How can laser projection profilometry be applied to enable 3D reconstruction and unsupervised segmentation for defect identification in drinking water pipelines?

1. How can accurate 3D reconstruction be achieved from LPP data in drinking water pipelines?
 - (a) What calibrations are required to compensate for distortion?
 - (b) How can the acquisition system and data processing be optimized for noisy conditions?
2. How can unsupervised learning methods be applied to segment reconstructed pipeline surfaces?
 - (a) Which clustering algorithms provide the most interpretable and stable segmentation results?
3. How can the quality of the segmentation and reconstruction be evaluated?
 - (a) What metrics can be used to assess physical relevance?
 - (b) How can segmented regions be visualized to support decision-making for integrity assessment?

The remainder of this thesis aims to answer the above questions and is structured as follows: [Chapter 2](#) consists of a systematic literature review identifying gaps in the literature, [Chapter 3](#) describes the experimental setup, [Chapter 4](#) describes the data processing pipeline and [Chapter 5](#) discusses the results, evaluates their performance, and interprets their implications for practical pipeline inspection. Finally, [Chapter 6](#) outlines the main conclusions, limitations, and recommendations for future research.

2

LITERATURE REVIEW

This chapter presents the methodology and findings of a systematic literature review. The methodology is detailed in [Section 2.1](#). The results are organized into two parts: the meta-analysis, including the inclusion and exclusion process in [Section 2.2](#), and a synthesis of the reviewed studies in [Section 2.3](#), and found research gaps in [Section 2.4](#).

2.1. METHODOLOGY

In order to provide an unbiased overview of the research landscape a predefined methodology [51] is used. The objective of this literature review is to provide an overview of recent methods for non-destructive optical pipeline inspection. This work incorporates optical sensing modalities such as [LRP](#), [LPP](#), structured light projection and standard illumination, [Light Detection and Ranging \(LiDAR\)](#) is not directly included. The following research questions are addressed:

1. [Camera calibration] - What methods are used to correct fish eye lens distortions in images in pipe-like or underwater environments?
2. [Reconstruction] - What methods are used to reconstruct the 3D geometry of pipes in optically inspected pipe-like interiors?
3. [Segmentation] - What segmentation approaches are used for defect segmentation in optically inspected pipe-like interiors?

Scopus¹ was used as the search channel due to its ability to search and access a wide range of scientific literature (including preprints) ensuring that a representative section of literature is evaluated in a systematic way. The following queries were used to create a search space in recent literature (2015-2025). The research questions formed the basis for the queries that expand upon them by including various variations of keywords or components.

1. TITLE(("distort*"OR"correct*"OR"calibrat*") AND ("camera"OR"lens*"OR"image*")) AND TITLE-ABS-KEY(fisheye AND ("water*"OR

¹<https://www.scopus.com>

- ```
"pipe*"OR"tube*"OR"circle"OR"underwater"OR"submerged")) AND
PUBYEAR > 2014 AND (LIMIT-TO(LANGUAGE,"English"))
```
2. TITLE("pipe\*"OR"tube\*") AND TITLE-ABS-KEY(("inner"OR"innard"OR"inside"OR"in-line"OR"surface") AND ("reconstruction"OR"profilometry") AND ("optical"OR"laser"OR"structured light")) AND PUBYEAR > 2014 AND (LIMIT-TO(LANGUAGE,"English"))
  3. TITLE(("segmentation"OR"clustering") AND ("tunnel"OR"pipe\*"OR"tube\*") AND ("feature\*"OR"defect\*"OR"surface"OR"inspect\*")) AND PUBYEAR > 2014 AND (LIMIT-TO(LANGUAGE,"English"))

Studies found through the queries are systematically screened with the purpose of evaluating their relevance for answering the research questions. This evaluation starts by summarizing each found study broadly based on the title, abstract and keywords. These summaries are used to evaluate if the below conditions are met, see [Appendix A](#) for the results. Additionally papers whose full text is unavailable under the UTwente license are excluded for practical reasons.

1. Relevance to at least one research question:
  - (a) *Camera calibration*: Methods for correcting (underwater) fisheye images.
  - (b) *Reconstruction*: Methods for 3D reconstruction from optical pipe internal data.
  - (c) *Segmentation*: Methods for segmenting defects from optical pipe internal data.
2. Domain relevance or method relevance:
  - (a) The application is fully underwater or in pipeline environments.
  - (b) Methods with plausible applicability in pipelines.

Backwards citation chaining (snowball) [52] was used on query results providing a more comprehensive overview with a single layer chain depth. Only papers that moved on to a full text evaluation are shown in the snowball results.

To ensure the validity of the findings, the quality of the all included studies was assessed based on their full texts, focusing on internal and external validity both quantitatively and qualitatively [53]. Furthermore to increase the quality of the outputted table grouping was done based on general categories extracted from the initial screening summarization with only the exclusion decision showcased on a per paper basis.

- **Internal Validity**: Subjectively assessed through a evaluation of the study methodology, including design, data collection, result evaluation and analysis. The aim is to identify potential biases or methodological weaknesses.
- **External Validity**: Used as a proxy for the generalizability of the study. This is quantitatively evaluated using the [Field-Weighted Citation Impact \(FWCI\)](#) and the total citation count. [FWCI](#) is selected due to its normalization across disciplines, publication types, and publication years, making it less sensitive to database coverage and more resistant to manipulation [53].

The evaluation and information extraction of the reviewed papers are conducted by a single author with subjectivity inherently present in the assessment process. While efforts were made to ensure consistency and transparency, personal interpretation may have influenced certain judgments. To partially mitigate this limitation, a standardized checklist was employed during the inclusion process, furthermore the evaluation was done systematically for papers across each research question and the results are listed per paper in each step in [Appendix A](#).

## 2.2. META ANALYSIS

[Figure 2.2](#) shows the temporal distribution of the 145 included items resulting from the queries (see [Figure 2.1](#) for the progression from search space to final review inclusion). Publications increased steadily after 2022 reflecting the rise of interest. In terms of geographical distribution ([Figure 2.3](#)), China is the most frequent country of affiliation (77 items), followed by the United States (20 items) and then a wide range of countries in various regions. Contributions are therefore concentrated in a few major research hubs, although the overall dataset spans more than 30 countries, indicating a globally distributed research landscape after the major two hubs.

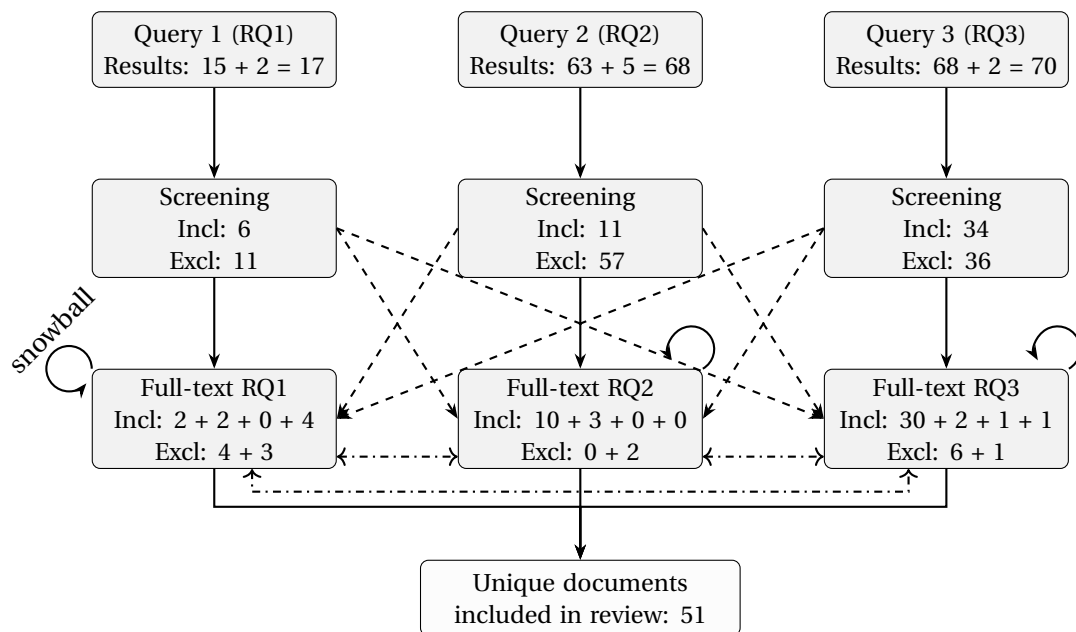


Figure 2.1: Study selection process by research question, where solid arrows indicate the main workflow, dashed arrows represent transfers between queries, and loop arrows denote snowballing. Query X: papers + preprints ; Full-text RQx inclusion: RQx screening + RQx snowball + RQyz screening + RQyz full text/snowball; Full-text RQx exclusion: RQx screening + RQxyz snowball/full text

### 2.2.1. JOURNALS

The search space is dominated by journal articles (100/145 items, 69%), with conference proceedings also contributing substantially (39/145, 27%). Book series contributions, and trade journals make up the rest (6/145, 4%). The review identified 100 items published across a broad range of journals. Most outlets were represented only once (59/100 items). A smaller group of journals accounted for multiple contributions (41/100 items), which are presented in [Table A.1](#).

Most journals are related to civil engineering and infrastructure or computer vision.

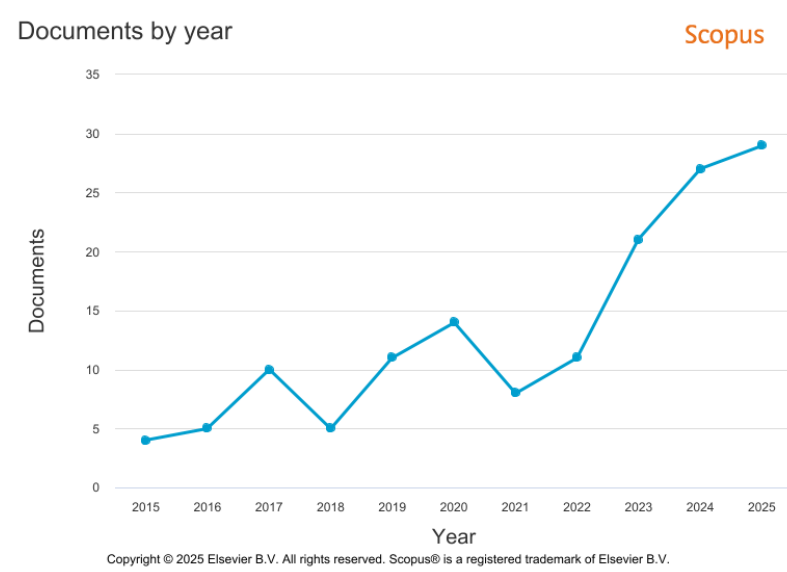


Figure 2.2: Publication date of found journal items.

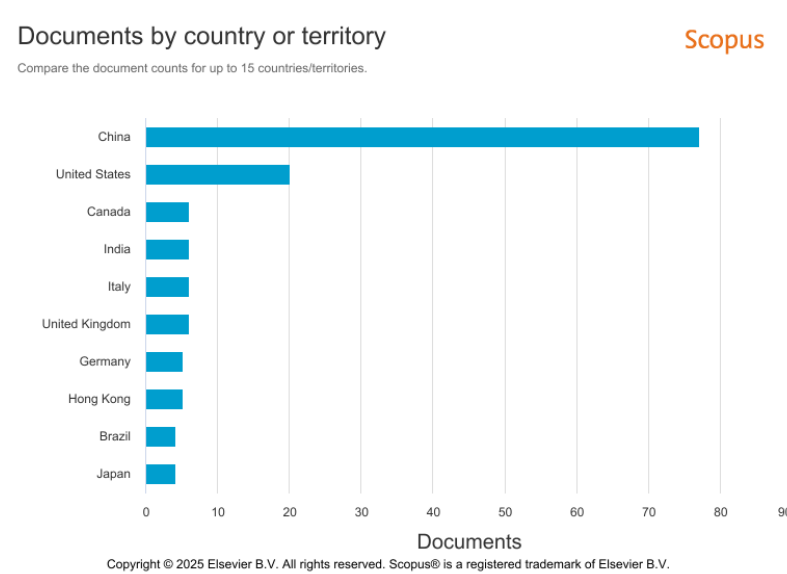


Figure 2.3: Publication origin of found journal items.

## 2.3. OPTICAL INSPECTION

This section reviews optical non-destructive [ILI](#) methodologies from 2015–2025, discussing the data processing pipeline from acquisition to 3D reconstruction and segmentation. [Subsection 2.3.1](#) presents a unified taxonomy, while [Subsection 2.3.3](#) introduces the identified sensing modalities. Subsequent sections, [Table 2.3.3](#) through [Figure 2.3.3](#), detail the methodological steps for each modality. Finally, [Subsection 2.3.2](#) examines the evaluation landscape and [Section 2.4](#) summarizes the identified research gaps.

### 2.3.1. METHODOLOGICAL TAXONOMY

The methodologies identified within [Section 2.3](#) are classified into a taxonomy summarizing the methodological choices made across the literature per modality as shown in [Figure 2.4](#). In [Figure 2.4](#) the progression from raw data acquisition (white boxes) to final structural analysis for the different sensing modalities (yellow boxes) is shown through categories (blue boxes).

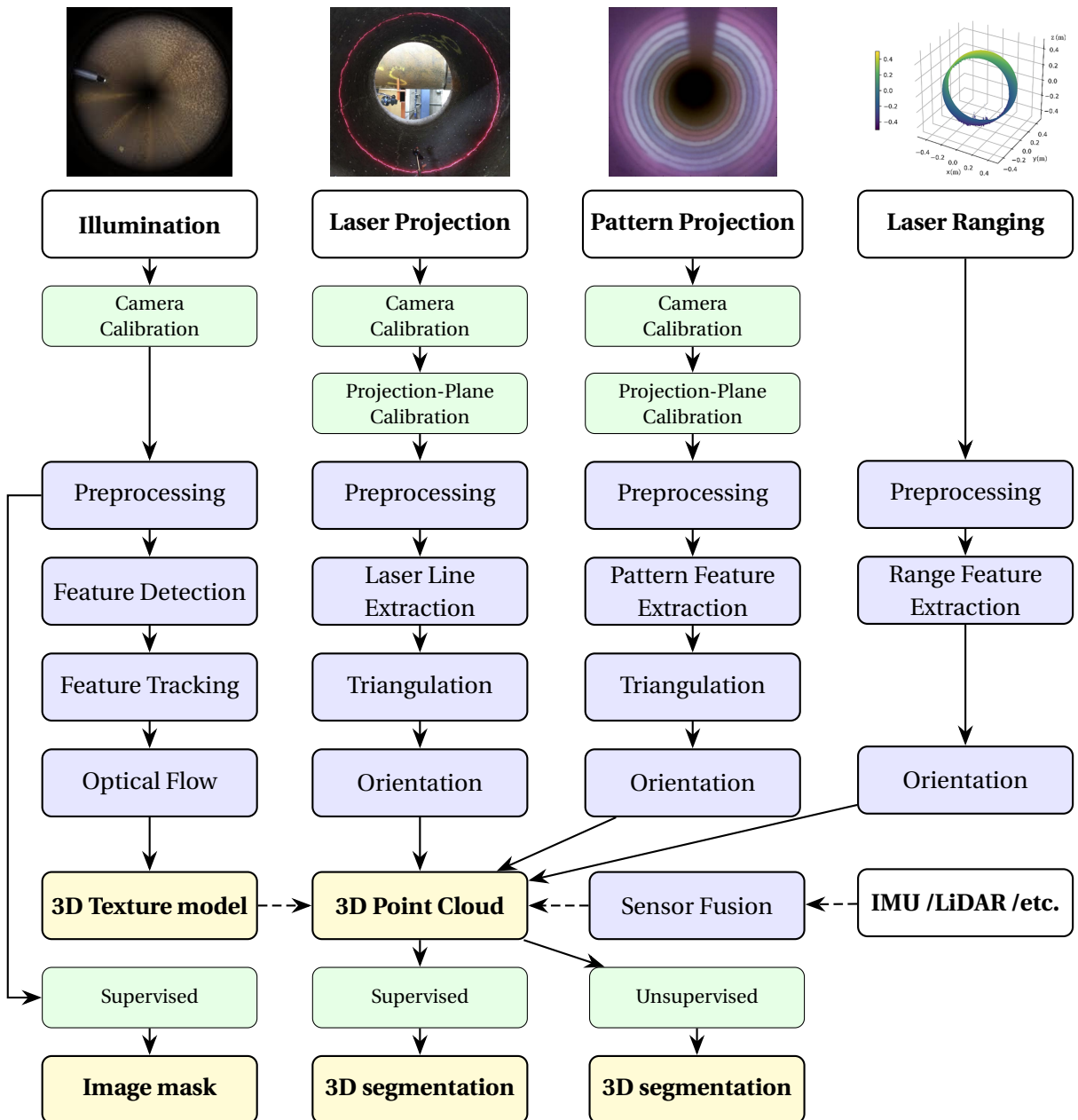


Figure 2.4: Non destructive optical ILI methodological taxonomy.

### 2.3.2. EVALUATION TECHNIQUES

Camera calibration is assessed via reprojection error [16, 17, 24, 54–57]. For 3D reconstruction and segmentation, performance is validated against ground truth obtained through manual pipe measurements [15, 16, 21, 28] or known geometry objects [14, 17, 18, 58]. Point cloud similarity is often computed using [Iterative Closest Point \(ICP\)](#) [17, 58]. Quantitative assessment for supervised [1, 19, 23, 31, 34–36, 42, 44, 47–49, 59–63] and unsupervised [21, 22, 64] segmentation relies on class based metrics like precision, recall, and F1, or geometric metrics such as IoU and pixel accuracy.

### 2.3.3. SENSING MODALITIES

Optical inspection systems acquire data through various different light emitters (laser, LED, structured light) and sensors (camera or other detector). The combination of the emitters and sensors leads to various modalities: Illumination (led + camera), Laser Projection (laser + camera), Laser Ranging (laser + time-of-flight sensor) and Pattern Projection (structured light + camera). These modalities determine the type of raw data available for processing and constrains the subsequent reconstruction and segmentation pipeline. [Table 2.1](#) summarizes the modalities present in the literature review and the amount of studies using them. Internal illumination (using incoherent light) is the most common and results in 2D images with texture and color [1, 4, 17, 27, 29–50, 57]. The second most common modality is laser (coherent monochromatic light) projection which can then be viewed on 2D images [12–19, 58]. Laser range sensing which directly outputs a (sparse) 3D point cloud is also used in various studies [1, 20–23, 59–64]. Pattern projection (structured light) is less common [28]. Furthermore optical methods are often combined with additional sensors ([LiDAR](#), [Inertial Measurement Unit \(IMU\)](#) etc.) [15, 17, 57] for motion estimation, depth estimation, [Simultaneous Localization and Mapping \(SLAM\)](#) or pose estimation. Interestingly none of the found studies reported inspection in filled pipes as all the studies tested in drained pipes with only a single study operating in an aquatic environment [58] (not [ILI](#)). Besides the sensing the transportation of the sensing modality is done using a [Remotely Operated Vehicle \(ROV\)](#), [Autonomous Underwater Vehicle \(AUV\)](#), cart, tube, [Pipeline Inspection Gauge \(PIG\)](#) and others which is summarized in [Table 2.1](#).

Table 2.1: Overview of sensing modalities used in optical pipe and tunnel inspection.

| Category                  | Description                               | Studies                   |
|---------------------------|-------------------------------------------|---------------------------|
| <b>Optical methods</b>    | Illumination                              | [1, 4, 17, 27, 29–50, 57] |
|                           | Laser projection                          | [12–19, 58]               |
|                           | Laser range sensing                       | [1, 20–23, 59–64]         |
|                           | Pattern projection                        | [28]                      |
| <b>Carrying platforms</b> | Tubular                                   | [12, 14, 16, 20, 28]      |
|                           | Wheeled carts                             | [15, 17, 18, 34]          |
|                           | <a href="#">ROV</a> / <a href="#">AUV</a> | [13, 58]                  |
|                           | Handheld/ <a href="#">PIG</a> /other      | [1, 4, 57]                |

## ILLUMINATION

Illumination-based inspection uses non coherent lighting to capture visual information from pipe interiors with a camera (see [Figure 2.5](#) and [Figure 2.6](#)) after which optical flow can be estimated or segmentation masks of defects can be produced, see [Table 2.2](#) for a summary of the data processing pipeline. Camera calibration was exclusively done in sensor fusion frameworks using varying methods [[17](#), [57](#)]. Preprocessing is rarely done but is used for noise reduction [[34](#)], feature enhancement [[57](#)] and data [[4](#)]. Feature detection is based on AKAZE [[65](#)], GFT [[66](#)] or CNN-derived features [[57](#)]. Tracking and feature matching is performed using LK [[67](#)], enabling motion estimation and 3D texture modeling [[4](#), [17](#), [57](#)]. Most do not build 3D texture models, instead directly going for segmentation on the images using supervised deep learning networks such as encoder/decoders, attention based and hybrid models [[19](#), [27](#), [29–50](#)]. Annotation strategies vary between manual labeling [[31](#), [34–36](#), [42](#), [47–49](#)] and automated or semi-automated methods such as the [Segment Anything Model \(SAM\)](#) for mask candidates [[44](#)], or even a human aided approach where [SAM](#) and YOLOv5 iteratively bootstrap the labeling process [[38](#)].

Table 2.2: Overview of illumination data processing methodologies.

| Step               | Methods                                                       | Studies                                                                              |
|--------------------|---------------------------------------------------------------|--------------------------------------------------------------------------------------|
| Camera calibration | Multi modal,                                                  | [ <a href="#">17</a> , <a href="#">57</a> ]                                          |
| Preprocessing      | GAN defogging, feature enhancement, unwrap                    | [ <a href="#">4</a> , <a href="#">17</a> , <a href="#">31</a> , <a href="#">34</a> ] |
| Feature detection  | AKAZE [ <a href="#">65</a> ], GFT [ <a href="#">66</a> ], CNN | [ <a href="#">4</a> , <a href="#">17</a> , <a href="#">57</a> ]                      |
| Feature tracking   | LK [ <a href="#">67</a> ]                                     | [ <a href="#">17</a> , <a href="#">57</a> ]                                          |
| 3D texture model   | Visual odometry accumulation                                  | [ <a href="#">4</a> , <a href="#">17</a> , <a href="#">57</a> ]                      |
| Segmentation       | Encoder/decoder, attention, region based                      | [ <a href="#">27</a> , <a href="#">29–50</a> ]                                       |



Figure 2.5: Wheeled cart with camera and LED [[17](#)].

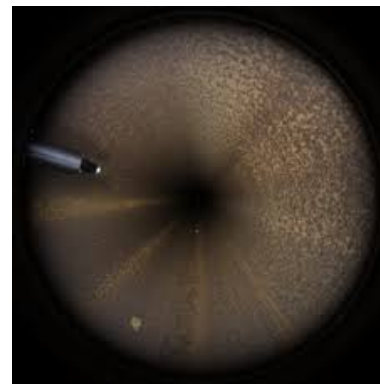


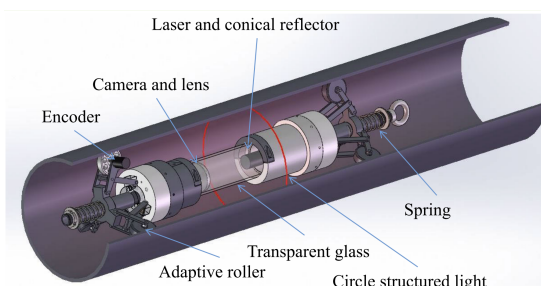
Figure 2.6: Illuminated pipe internal image [[17](#)].

## LASER PROJECTION

**LPP** uses a laser and a conical mirror to project a laser on the pipe interior. The resulting circular laser line is captured by the camera (see Figure 2.7 and Figure 2.8) after which data processing enables the extraction of pipe-wall surface geometry, see Table 2.3 for an overview. Calibration includes both camera calibration [13–18, 58, 68] and laser-plane calibration [13–18, 58, 68]. Pre-processing removes noise (gaussian [13], side window [69] filtering [16], DBSCAN[21]), reduces data size using binarization [12, 13] and crops to a **Region of Interest (ROI)** [13, 19, 21]. Laser line extraction mostly uses intensity-based approaches [13, 58], Steger’s[70] method [14, 16], Gaussian fitting [21] and HSV thresholding [17] however deep learning [58] and distance based [12, 18] approaches are also used. Triangulation reconstructs 3D coordinates via ray–plane intersection [13–18, 58, 68]. Orientation correction estimation uses ellipsoid fitting [20], hardware alignment [14, 16] or **ICP** [18]. 3D frames are stacked or registered into a 3D point cloud [12–18, 21, 58]. The resulting 3D point clouds can then be segmented just like any other 3D point cloud, however none of the papers segmented the **LPP** sourced 3D point cloud. Some did manually identify defect from the **ROI** resulting from visualization colorization based on radius, curvature among other color encoded features [12–14, 18]. Furthermore a single paper performed supervised segmentation on the raw laser projection images instead with manual annotation [19], skipping 3D reconstruction.

Table 2.3: Overview of laser projection data processing methodologies.

| Step               | Methods                                        | Studies                  |
|--------------------|------------------------------------------------|--------------------------|
| Camera calibration | Intersection with planar target [24, 71–74]    | [12–18, 68]              |
| Triangulation      | Plane intersection [24, 75]                    | [13–18, 58, 68]          |
| Preprocessing      | Noise removal, binarization, <b>ROI</b> crop   | [12, 13, 13, 16, 19, 21] |
| Laser extraction   | Intensity, distance and CNN                    | [12–14, 16–18, 21, 58]   |
| Orientation        | Circle/ellipsoid fitting, hardware, <b>ICP</b> | [14, 16, 18, 20, 21]     |
| 3D point cloud     | Longitudinal stacking                          | [12–18, 21, 58]          |
| Segmentation       | Encoder/decoder with transfer learning         | [19]                     |

Figure 2.7: Tubular inspection robot for **LPP** [14].Figure 2.8: Image acquired with **LPP** [18].



LASER RANGING

Laser-ranging systems measure radial distance directly by measuring the time it takes for the reflection to return (see Figure 2.9 and Figure 2.10). Preprocessing is an essential step to reduce noise in the point cloud and is done using methods such as k-means [22], DBSCAN[21] and manual filtering [64]. Furthermore various studies also unwrap the data for further processing [59, 63]. The geometric center of a slice typically deviates from the center of the coordinate system due to the scanner's arbitrary position during measurement [21]. In order to align the slice the center needs to be extracted. This can be done using least-squares- [21, 59] or RANSAC [22] circle fitting. Orientation is then corrected using alignment correction sourced from other sensors [20] or by calculating the alignment correction through fitting on a sphere or cylinder [21, 22]. Stacking is used to combine the 2D slices into a 3D point cloud. Segmentation is achieved with supervised deep learning [1, 23, 59–63] or unsupervised clustering methods such as DBSCAN, BCSF and DRG [21–23]. Of all these studies most performed supervised point cloud segmentation both in pipes and tunnels, purely in pipes two performed supervised based segmentation [1, 23] and two performed unsupervised segmentation [21, 22].

Table 2.4: Overview of laser range data processing methodologies.

| Step                      | Methods                           | Studies           |
|---------------------------|-----------------------------------|-------------------|
| Preprocessing             | Noise reduction (DBSCAN, k-means) | [21, 22, 64]      |
| Slice alignment           | least squares/RANSAC circle fit   | [21, 22, 59]      |
| 3D point cloud            | Longitudinal stacking             | [1, 20–23, 59–64] |
| Supervised Segmentation   | Graph/Attention/Mask/UNet         | [1, 23, 59–63]    |
| Unsupervised Segmentation | DBSCAN, BCSF, DRG, upsampling     | [21, 22, 64]      |

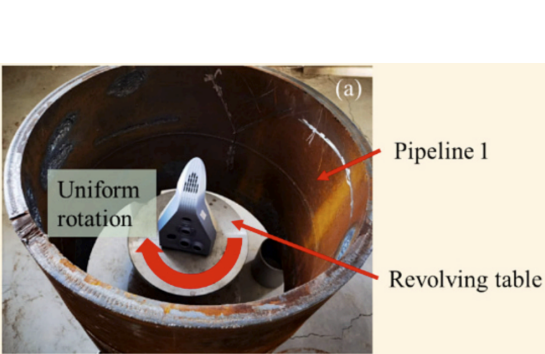


Figure 2.9: Laser range scanner in a pipe [22].

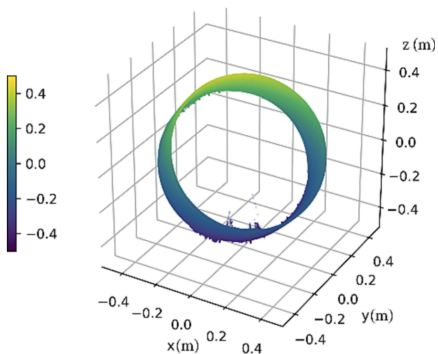


Figure 2.10: Point cloud from laser ranging [21].

## PATTERN PROJECTION

Pattern-projection systems use structured patterns (see Figure 2.11 and Figure 2.12) for profiling the pipe surface and depth estimation. Camera and projector geometry are calibrated using a custom methodology which is based on a conical ray plane intersection [28]. Preprocessing consists of Gaussian low pass filtering and median filtering on the images and then transforming them into a polar domain [28]. The centerline is extracted by finding the edges which is done by calculating the gradient across the image after applying a smoothed gradient kernel [28]. The edges are then used to find the centerline in between the projections using the intensities [28]. Orientation of each cross-section is determined through ellipsoid fitting [28].

Table 2.5: Overview of pattern projection data processing methodologies.

| Step                         | Methods                              | Study |
|------------------------------|--------------------------------------|-------|
| Camera calibration           | Pinhole                              | [28]  |
| Projection-plane calibration | Pattern-projector geometry           | [28]  |
| Preprocessing                | Noise reduction, feature enhancement | [28]  |
| Pattern extraction           | Edge/gradient methods                | [28]  |
| Triangulation                | Ray-plane intersection               | [28]  |
| Orientation estimation       | Ellipsoid fit                        | [28]  |
| 3D Point cloud               | Longitudinal stacking                | [28]  |

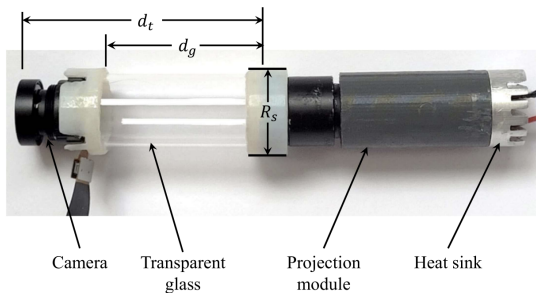


Figure 2.11: Example pattern projection hardware [28].

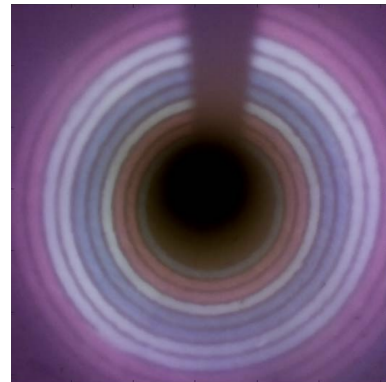


Figure 2.12: Example pattern projection image [28].

## 2.4. GAPS IN THE LITERATURE

The review found no studies processing data in filled pipelines or segmenting point clouds from LPP or pattern-projection. Existing segmentation in pipe settings is dominated by image based deep learning, while point cloud cases (LRP sourced) primarily utilize deep learning or DBSCAN with DRG. Laser extraction for LPP remains limited to intensity-based filtering. Only one study [19] performed segmentation directly on LPP source images, and without 3D reconstruction. This gap likely exists due to the real world limitations reflections and scattering in pipes complicate the geometric consistency required for automated 3D reconstruction. This work therefore investigates alternative LPP laser-extraction methods and applies unsupervised clustering to the resulting point clouds.

# 3

## CASE STUDY SET-UP

This chapter provides a detailed description of the setup used to acquire data and how it supports quantitative evaluation. The chapter is structured to first present the physical hardware and test environment, followed by a discussion of the data acquisition. Specifically, [Section 3.1](#) introduces the inspection robot and its optical sensor configuration. In [Section 3.2](#) the controlled test setup used to simulate real pipeline conditions is discussed. Subsequently, [Section 3.3](#) discusses the acquisition of real images in the aforementioned test setup. Lastly [Section 3.4](#) discusses the generation of synthetic datasets.

### 3.1. ROBOT

The robot is designed and produced by Rosenxt<sup>1</sup> with the goal of non-destructive [ILI](#) of drinking water pipelines. In this work solely the optical data acquisition part of the robot will be discussed. It consists of a wide angle camera and a green laser which projects a laser line using a conical mirror, the concept is similar to [\[14, 28\]](#). This results in high resolution images with a circular laser line. An example robot showcased in [Figure 3.1](#) (example is multicam while robot used in this work is monocam) with the corresponding optical geometry shown in [Figure 3.2](#).

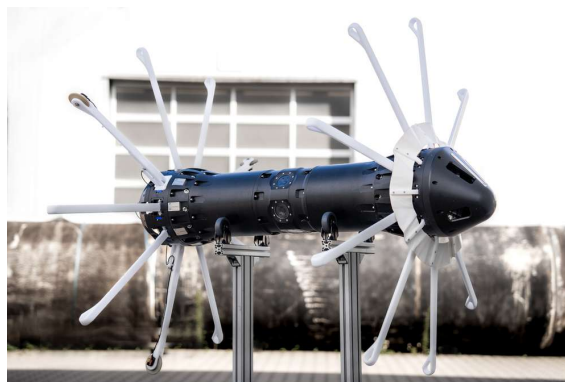


Figure 3.1: Example robot: [Linegy](#)

---

<sup>1</sup><https://www.rosen-nxt.com/en>

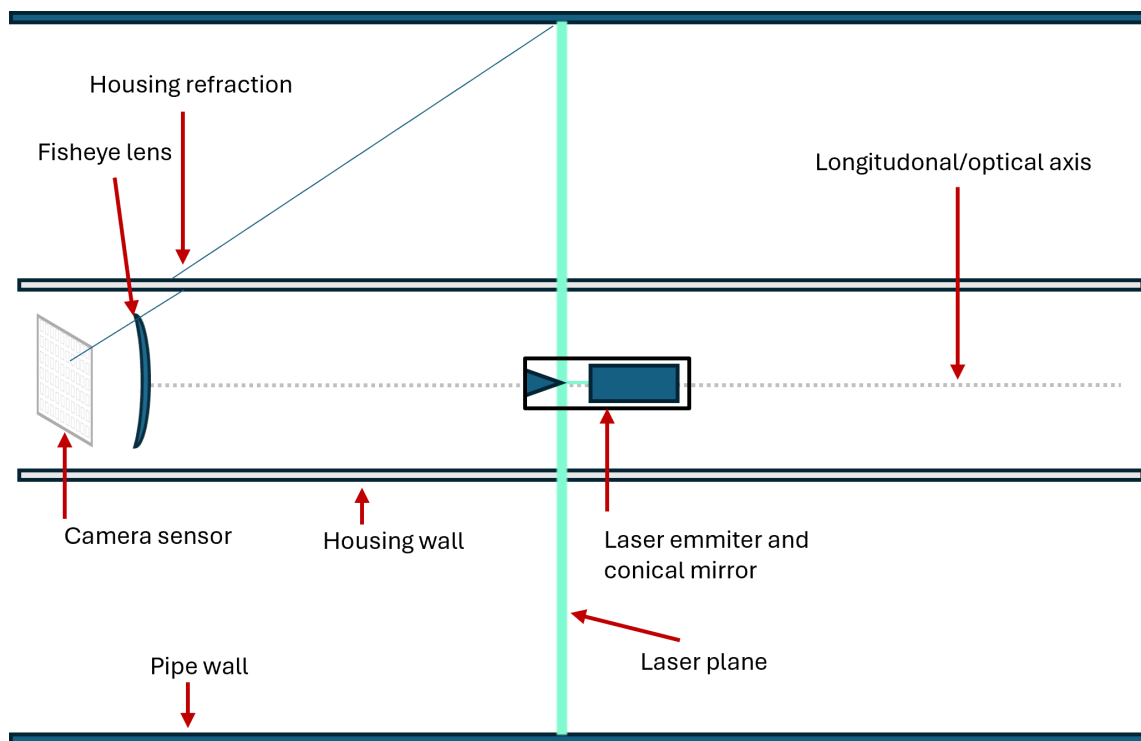


Figure 3.2: Camera and laser reflection geometry. Similar to [14, 28].

### 3.2. TEST SETUP

In order to evaluate the system a test setup was provided by Rosenxt<sup>2</sup> with the goal of simulating real drinking water pipeline conditions. The test setup consisted of a barrel with space for a pipe (Figure 3.3). The pipe was centered and fastened in the barrel using wood blocks. The robot was manually inserted into the the pipe inside of the barrel with the aim of achieving a constant speed and alignment (aided by a stabilizing insertion structure). The barrel was darkened by preventing the entry of ambient light from the outside. Due to the manual manner of testing the speed, pitch, yaw and roll were not completely constant or absent. Figure 3.3 showcases the barrel, darkening foil (exterior) and the concrete blocks onto which the pipe is placed.



Figure 3.3: Barrel test setup into which other pipes were placed and the robot was lowered into from above.

<sup>2</sup><https://www.rosen-nxt.com/en>

Several artificial defects are introduced including blocks (Figure 3.4) and an evaluation plate with slits, holes, screws, and 3D printed objects (Figure 3.5). Defects are created from (coated) stainless steel and plastic. These defects with known or measurable geometry allow for a controlled evaluation of the system's ability to detect and quantify pipeline anomalies. Furthermore another test was done in an oval form (Figure 3.6).

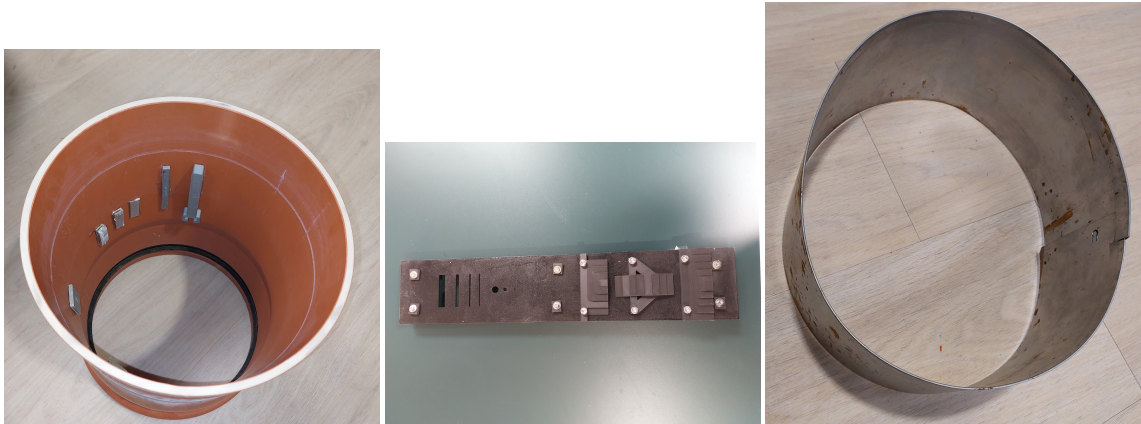


Figure 3.4: Blocks in the PVC pipe. Figure 3.5: Coated evaluation plate. Figure 3.6: Oval metal form.

### 3.3. ACQUIRED DATA

Pipelines geometrically are circular or oval. Due to this property and the properties of the camera and laser geometry (see Figure 3.2) the reflection of the laser planes against the pipe wall are captured as a set of concentric circles as showcased in Figure 3.7.

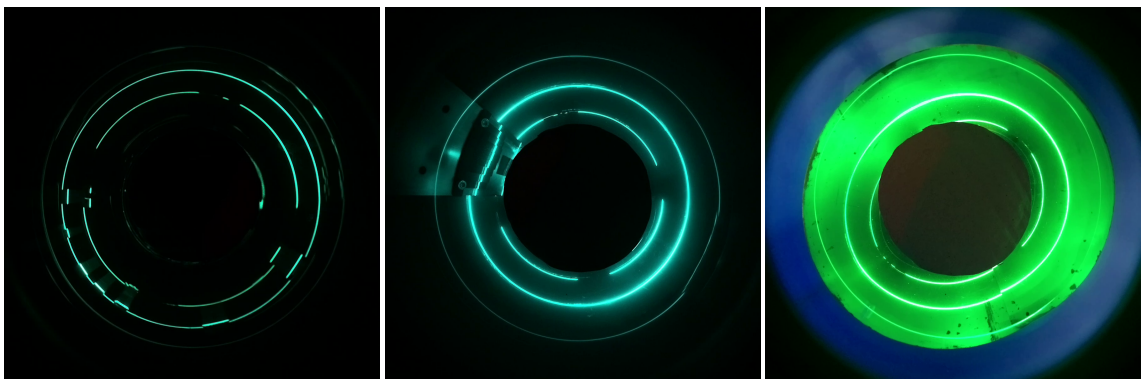


Figure 3.7: Example data: block deformations (left), the evaluation plate (middle) and the metal oval (right).

### 3.4. SYNTHETIC DATA

Synthetic data is generated in order to simulate the appearance of real images and to provide a reliable basis for quantitative evaluation. Depending on the experiment, the synthetic generator uses either random parameters or user-provided parameters. The user provided parameters also allow for the generation of a quasi synthetic point cloud that approximates a real pipe using specified parameters. Figure 3.8 illustrates the following supported defects.

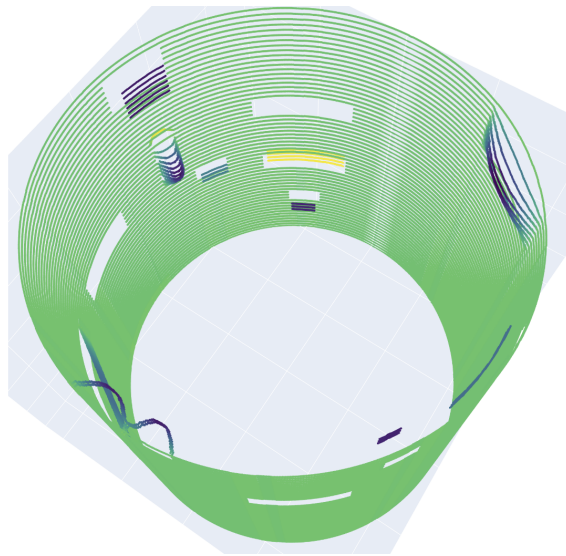


Figure 3.8: Randomly generated synthetic point cloud with slits (i.e. gaps), radial blocks, flat blocks and dents.

The generation process starts with a binary mask that defines the shape of the provided lasers. The mask contains the defect contours (radial changes or gaps) and the order in which a defect becomes visible is also taken into account which simulates a forward-facing (or backward-facing) data acquisition. This mask is then used to generate a synthetic image and a corresponding synthetic point cloud as described in [Subsection 3.4.2](#).

#### 3.4.1. SYNTHETIC IMAGES

The binary mask is used to generate representative images in 2D grayscale, see [Figure 3.9](#). The binary mask already contains the defects in the form of arch wise radial changes or gaps, thus in order to generate an synthetic image from this mask the following steps are applied:

- Global thickening of the laser line
- Randomly shifting the concentric circle center within the [FOV](#)
- Random local arch intensity reductions
- Global speckle noise
- Global gaussian blurring

#### 3.4.2. SYNTHETIC POINT CLOUDS

The binary mask is also used to convert the defect representation into a point cloud; this synthetic "ground truth" point cloud is used for evaluation purposes on the synthetic datasets. The mask is first transformed to polar coordinates as described in [Subsection 4.4.3](#). Since the polar transform may introduce local artifacts, padding and morphological operations described in [Section 4.8](#) are applied to reduce the scaled polar binary mask to a one-pixel wide representation. This 2D representation is then converted into a point cloud as illustrated in [Figure 3.10](#).



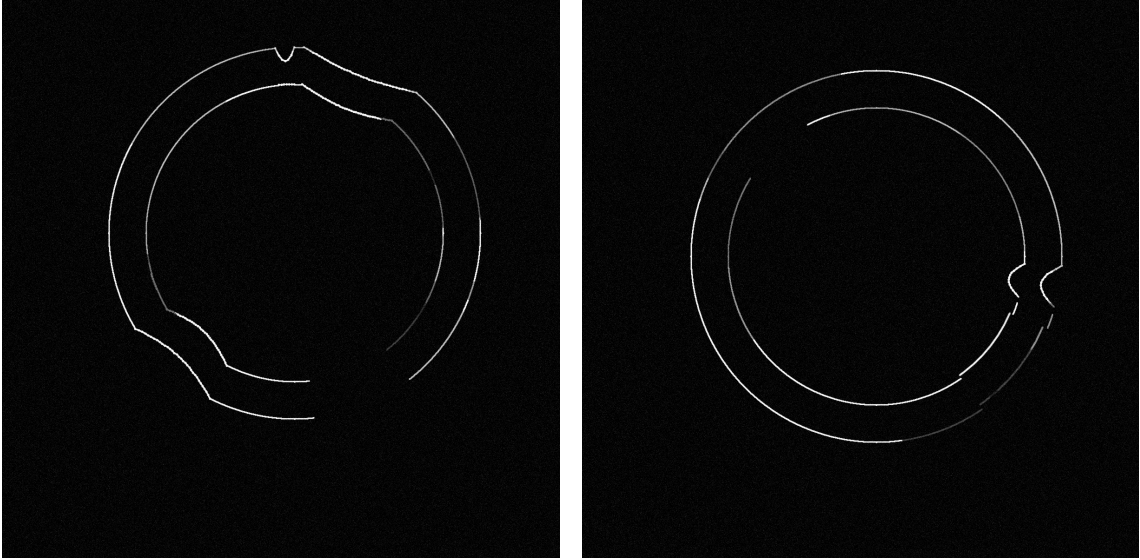


Figure 3.9: Two example synthetic images with deformations and noise present.

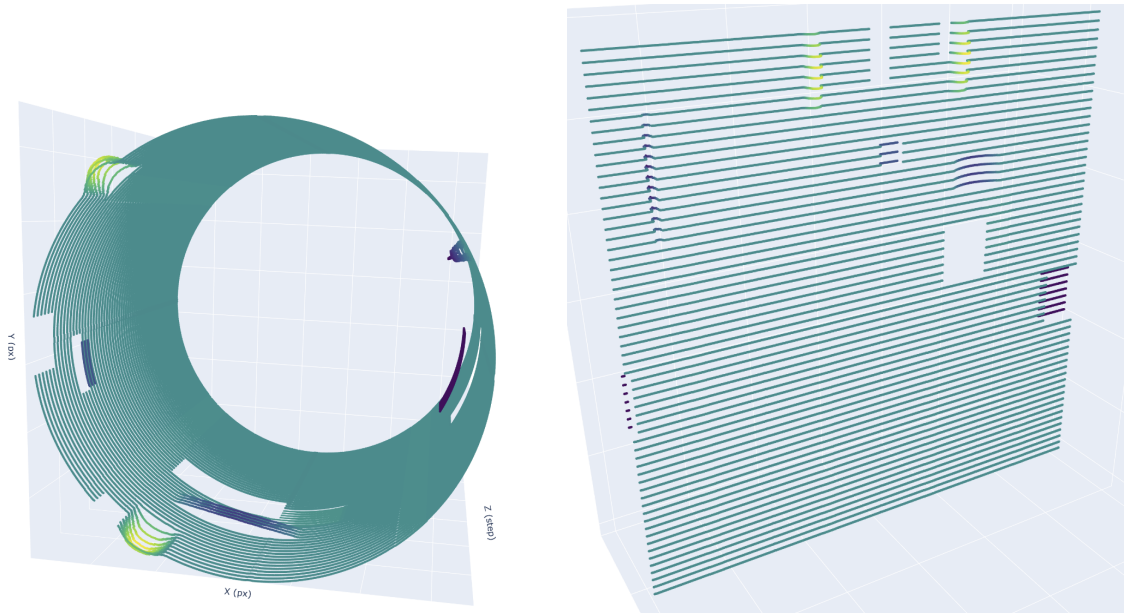


Figure 3.10: Example synthetic point clouds based on the binary mask (in cartesian and polar coordinates respectively).

# 4

## METHODOLOGY

This chapter outlines the methodology used in the [LPP](#) system for 3D reconstruction and segmentation. The methodology is structured in two parts. First, the research framework that guided the development and refinement of the processing steps is discussed. Second, the processing pipeline is presented, followed by detailed descriptions of each method in [Section 4.3](#) to [Section 4.7](#).

### 4.1. DATA MINING METHODOLOGY FOR ENGINEERING APPLICATIONS

The [Data Mining Methodology for Engineering Applications \(DMME\)](#) model [76] is an extension of the widely used [CRoss Industry Standard Process for Data Mining \(CRISP-DM\)](#) framework [77]. While [CRISP-DM](#) [77] provides a general structure for data-driven projects, it is not tailored to the particular constraints of engineering applications, where data acquisition, sensor behavior, and domain-specific performance requirements play a role. [DMME](#) [76] addresses these gaps by expanding the [CRISP-DM](#) model [77] with three additional engineering-oriented steps that account for the bridge between business and technical goals, measurement concepts, experimental design, data generation, data characteristics and long term testing which matches better with the more iterative nature of algorithm development in technical domains where the data is not fixed and might change over time as the algorithms, hardware and subsequently the data change.

In this study, [DMME](#) [76] served as the guiding methodology for designing and refining the complete data processing pipeline, from raw laser-projection image acquisition to 3D reconstruction and segmentation. Its iterative structure supported incremental improvements to the preprocessing, reconstruction and segmentation algorithms, enabling methodical progression from initial feasibility tests to a stable and validated processing pipeline with added knowledge about the limitations of the overall system.

The following list (visually represented in [Figure 4.1](#)) provides a comprehensive summary of the 9 steps present in the [DMME](#) [76] framework:



1. Business Understanding: Define the project's objectives and requirements from a business perspective and translate them into a clear business problem and preliminary plan.
2. Technical Understanding: Transform business goals into measurable technical goals, analyze the system, define target variables, gather existing expertise, and develop an experiment plan.
3. Technical Realization: Test and select measuring concepts, execute the experiment plan, and generate data while documenting limitations, error sources, and data quality.
4. Data Understanding: Collect and explore the data to identify quality issues and understand dataset completeness.
5. Data Preparation: Construct the final dataset from raw data through cleaning, transformation, and feature engineering.
6. Modeling: Deploy and calibrate analytical models on the prepared dataset to achieve optimal performance.
7. Evaluation: Assess models to ensure alignment with business objectives and select the final model for deployment.
8. Technical Implementation: Provide run-time data to the evaluated model by implementing long-term, robust sensor and software infrastructure.
9. Deployment: Go live with the final model in the production environment according to business requirements, from reports to complex data-driven infrastructures.

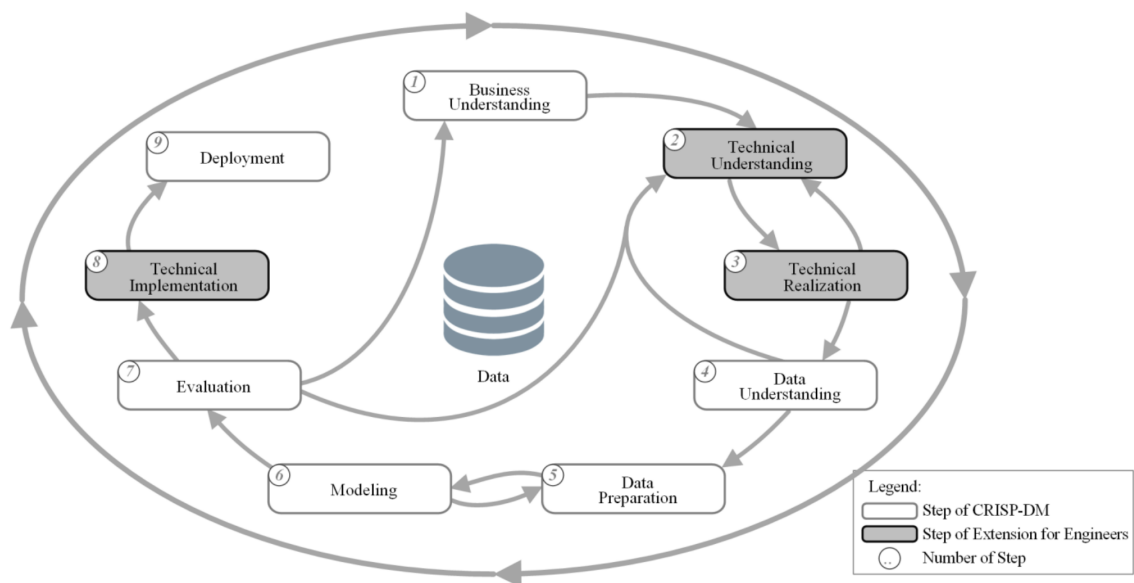


Figure 4.1: The DMME process [76].

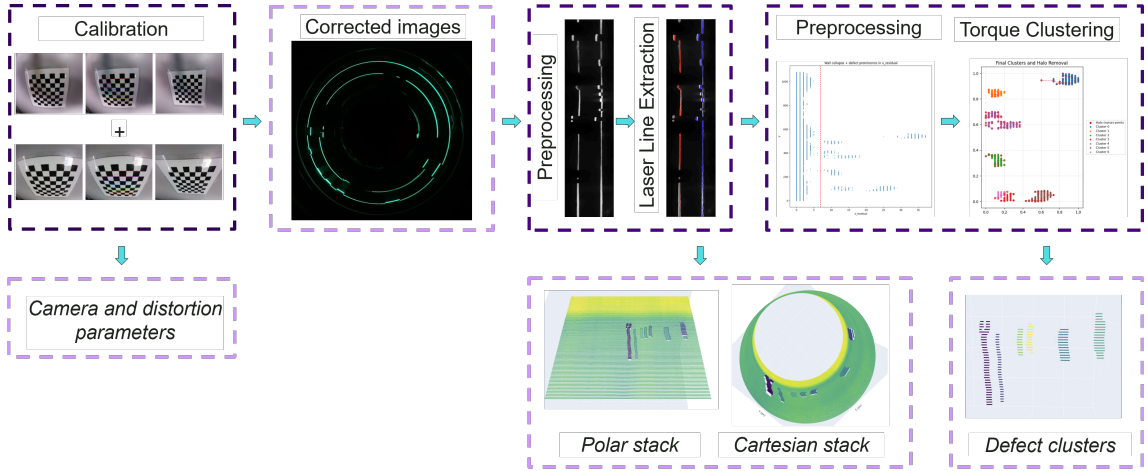


Figure 4.2: Data processing pipeline overview. Lavender: results; purple: methodological categories

## 4.2. PIPELINE OVERVIEW

The proposed **LPP** system transforms raw laser–projection images into structured 3D reconstructions and segmented point clusters. This transformation requires addressing several challenges: fisheye distortion, weak and noisy images, deformations in contours, missing contour segments, changing intensities in contours, contour diffusion, data size, and the need for consistent point extraction. First, camera calibration is required (once given that the hardware does not change) to allow for correction of images. Then for each image, preprocessing takes place after which the laser lines are extracted. The extracted laser lines are subsequently stacked into a point cloud. The point cloud is preprocessed and then segmented to extract defect clusters. The entire process is summarized visually in Figure 4.2. The next sections will explain the individual categories.

## 4.3. CAMERA CALIBRATION

Accurate geometric correction is required before further image processing. As the **LPP** system uses a wide-angle lens with barrel distortion, the classical pinhole model [24] is invalid. Calibration therefore uses the OpenCV fisheye model [56]<sup>1</sup>, which captures the radial distortion of fisheye lenses. Checkerboard images provide 2D–3D point correspondences [24] for estimating the intrinsic matrix  $\mathbf{K}$  and distortion coefficients  $\mathbf{D}$ . The fisheye projection maps the incident ray angle  $\theta$  to a distorted radius via a polynomial model [56], and the intrinsic parameters  $(f_x, f_y, u_0, v_0)$  map this to pixel coordinates, as in Equation 4.1. Inverse fisheye projection then undistorts the data, yielding geometrically corrected images.

$$\mathbf{K} = \begin{bmatrix} f_x & 0 & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} \quad (a) \quad \mathbf{D} = [k_1, k_2, k_3, k_4]^T \quad (b) \quad (4.1)$$

<sup>1</sup>[https://docs.opencv.org/4.x/db/d58/group\\_\\_calib3d\\_\\_fisheye.html](https://docs.opencv.org/4.x/db/d58/group__calib3d__fisheye.html)

#### 4.4. IMAGE PREPROCESSING

This stage aims to improve image features and reduce data size before laser line extraction takes place. An edge-preserving filter is used to smooth out speckle noise and enhance the edges in the image. The smoothed image is converted to grayscale, after which a concentric circle finding algorithm is used to find the coordinates of the laser circles. The found center is used to transform the image into polar coordinates after which a 1D cropping operation reduces data size by cropping towards the ROI resulting in a polar strip. This section is summarized visually in Figure 4.3.

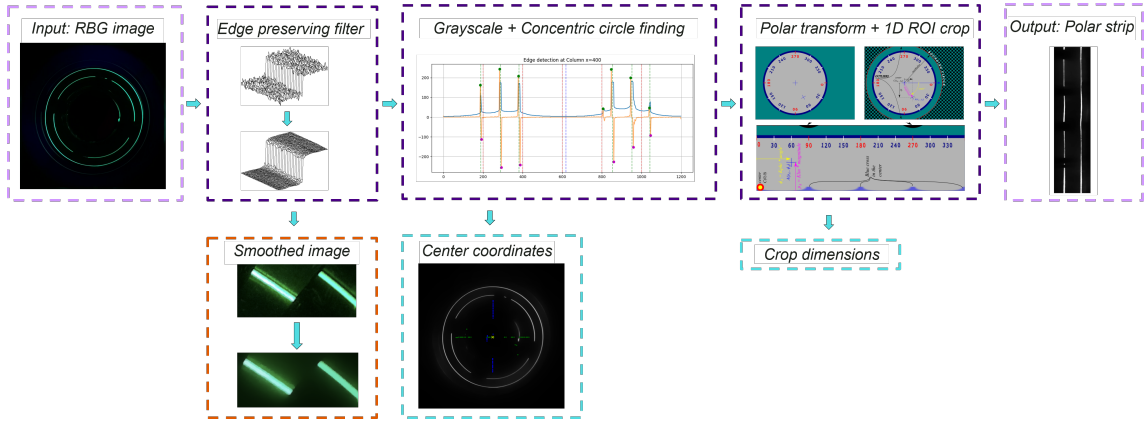


Figure 4.3: Image preprocessing pipeline. Lavender: inputs/outputs; purple: processing steps; turquoise: intermediate results; orange: temporary results.

##### 4.4.1. EDGE-PRESERVING FILTER

The edge-preserving filter in OpenCV<sup>2</sup>[78] performs edge-aware smoothing by mapping the image from its original coordinate system into a 1D domain where distances reflect both spatial proximity and color similarity. In this transformed space, obtained by unfolding the image surface formed by spatial coordinates and RGB values into a curve (see Figure 4.4a–c), pixels separated by strong edges lie far apart, while those in smooth regions remain close. A 1D smoothing operation performed along this domain (see Figure 4.4d) therefore blurs similar areas while preserving sharp transitions when mapped back to the image (see Figure 4.4e). For 2D images, the method applies horizontal and vertical 1D filtering.

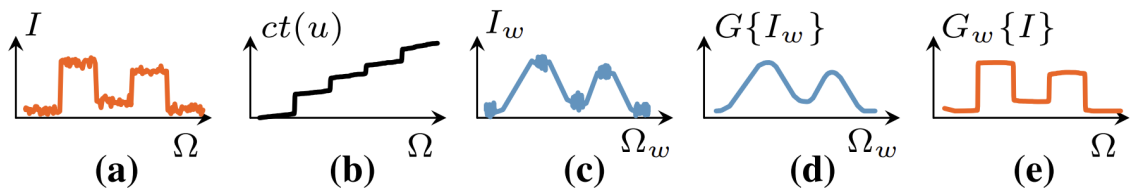


Figure 4.4: 1D edge-preserving filtering using  $ct(u)$ . (a) Input signal  $I$ . (b)  $ct(u)$ . (c) Signal  $I$  plotted in the transformed domain ( $\Omega_w$ ). (d) Signal  $I$  filtered in  $\Omega_w$  with a 1D Gaussian (e) plotted in  $\Omega$ . [78]

<sup>2</sup>[https://docs.opencv.org/4.x/df/dac/group\\_\\_photo\\_\\_render.html#gafaae2977597029bc8e35da6e67bd31f7](https://docs.opencv.org/4.x/df/dac/group__photo__render.html#gafaae2977597029bc8e35da6e67bd31f7)

#### 4.4.2. GRID-BASED CONCENTRIC CIRCLE CENTER DETECTION

This work uses a grid-based algorithm for estimating the pixel-wise center of 1 to  $n$  concentric circles, even when contours are partially missing, distorted or non-circular. The approach builds on the calibration pattern center extraction method of [79], adapting it to operate reliably under deformation. Synthetic examples are shown in Figure 4.6. A grid of  $m$  rows and  $n$  columns scaled with image size is placed on the image.

For each row and column, a 1D intensity profile is extracted (see Figure 4.5) and convolved with a Gaussian derivative to highlight rising and falling edges (orange curves). Peak detection (Subsection 4.5.1) yields candidate edge locations that are subsequently paired only when an opposite-signed partner lies within a spatial threshold. Additional filtering in the original intensity domain suppresses derivative only peaks, leaving only the valid ones (as in Figure 4.5). Each accepted pair defines a laser point.

The resulting laser points are sorted and split into left/right or top/bottom groups using a pre-defined gap parameter that represents the central region where no reliable signal is expected. When sufficient laser points exist on both sides, the innermost pairs are used to compute the row- or column-wise midpoint estimate, illustrated in Figure 4.5. Repeating this procedure across all rows and columns yields a collection of center candidates in both axes (Figure 4.6). Instead of averaging [79] this work uses the median to improve robustness to missing arcs, deformations, and outliers as a defect introduces bias for the center in a certain direction, see the midpoints being biased in the rows and columns with defects in Figure 4.6. The final estimated center is shown by the yellow cross in Figure 4.6.

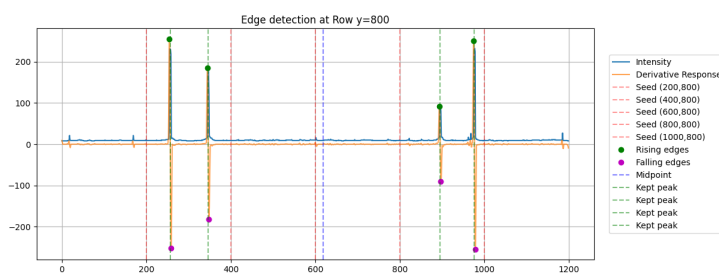


Figure 4.5: 1D row representation with four peaks.

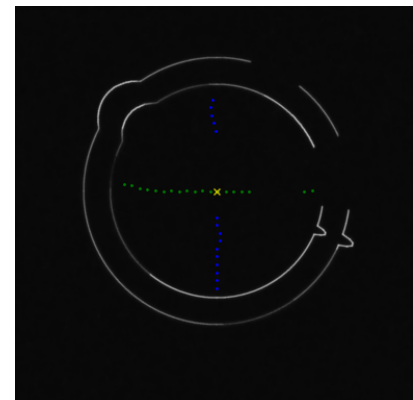


Figure 4.6: Row (blue) and column midpoints (green), and center (yellow).

#### 4.4.3. LINEAR SCALED POLAR TRANSFORM

Several stages of the proposed pipeline benefit from representing the image in a polar coordinate system rather than the conventional Cartesian form. The linear scaled polar transform remaps each pixel from the image  $(x, y)$  into the polar domain  $(\rho, \phi)$  around a center  $(x_c, y_c)$  in the original image. For a pixel located at  $(x, y)$  in the input image, the distance from the center  $r = \sqrt{(x - x_c)^2 + (y - y_c)^2}$  and the angular position  $\theta = \arctan2(y - y_c, x - x_c)$  are computed, see Figure 4.7. Then  $r$  and  $\theta$  are linearly scaled to define the coordinates in the transformed polar image.  $W$  and  $H$  denote the width and height of the image and  $R_{\max}$  represents the maximum radius. Under this mapping, a circle of constant radius in the Cartesian image is converted into a horizontal line in the  $(\rho, \phi)$  domain, while angular variations are represented along the orthogonal axis, see Figure 4.8.

$$\rho = K_r r \quad (a) \quad \phi = K_\theta \theta \quad (b) \quad K_r = \frac{W}{R_{\max}} \quad (c) \quad K_\theta = \frac{H}{2\pi} \quad (d) \quad (4.2)$$

The linear scaled polar transform is implemented using the polar image transformation functions provided by the OpenCV library<sup>3</sup>. The inverse mapping, which projects a point in the polar image back into the Cartesian domain, is defined below where  $(x_c, y_c)$  denotes the original center used during the transformation.

$$\theta = \frac{\phi}{K_\theta} \quad (a) \quad r = \frac{\rho}{K_r} \quad (b) \quad x = r \cos \theta + x_c \quad (c) \quad y = r \sin \theta + y_c \quad (d) \quad (4.3)$$

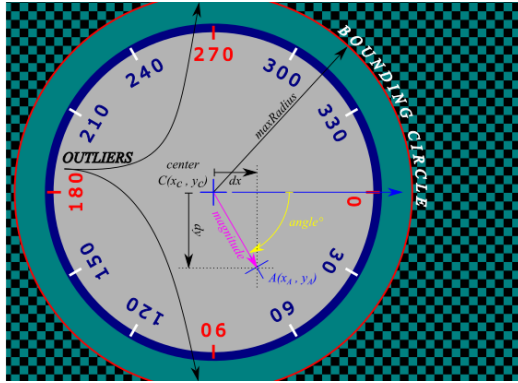


Figure 4.7: Cartesian reference

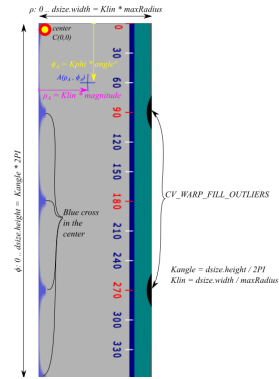


Figure 4.8: Polar reference

#### 4.4.4. REGION OF INTEREST

The ROI in this study is a simple horizontal crop[13, 21] of the polar-transformed image  $I \in \mathbb{R}^{H \times W}$ . The cropping region is defined by normalized width fractions  $\alpha, \beta \in [0, 1]$  with  $\alpha < \beta$ , yielding pixel indices  $x_0 = \lfloor \alpha W \rfloor$ ,  $x_1 = \lfloor \beta W \rfloor$ , and the cropped region  $I_{ROI} = I[:, x_0 : x_1]$ . The crop is *inclusive* of  $x_0$  and *exclusive* of  $x_1$ , consistent with Python slicing semantics.

<sup>3</sup>[https://docs.opencv.org/4.x/da/d54/group\\_\\_imgproc\\_\\_transform.html#ga49481ab24fdaa0ffa4d3e63d14c0d5e4](https://docs.opencv.org/4.x/da/d54/group__imgproc__transform.html#ga49481ab24fdaa0ffa4d3e63d14c0d5e4)

## 4.5. LASER EXTRACTION

This section describes the methods used to extract points from the images and processing these points into a 3D point cloud. This consists of first extracting rows wise intensity peaks in the polar strips after which a directional cost graph is computed based on these points. Start and end points for each expected laser line are then computed using 1D k-means after which A\* is used to find a path in the graph between the found start and end points. This results in separated points for each laser line (1...n). These 2D frame wise points are then stacked into a 3D point cloud along the longitudinal axis. This section is summarized visually in Figure 4.9.

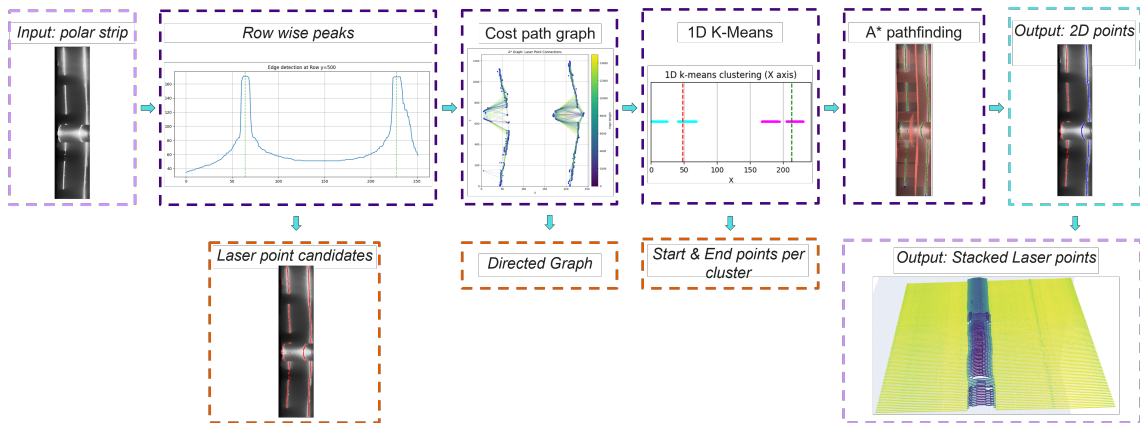


Figure 4.9: Image laser point extraction pipeline. Lavender: inputs/outputs; purple: processing steps; turquoise: intermediate results; orange: temporary results.

### 4.5.1. FIND PEAKS

Peak detection is used to identify significant local extrema in 1D signals in the polar transformed images. As polar transform introduces artifacts a more generic and less strict method differing from Subsection 4.4.2's method is applied directly onto the signal (not the derivative). Constraints such as minimum prominence, -width, and -distance between peaks is used to suppress detections noise. The implementation used is from SciPy<sup>4</sup>.

### 4.5.2. GRAPH CONSTRUCTION

For many path finding algorithms it is required to have points in a directed graph. Each point is a node in the graph. Edges are only created in the forward direction with respect to the  $y$ -axis, meaning that a node is connected exclusively to nodes whose  $y$ -coordinate is greater than its own, preventing the graph becoming cyclic. The existence of an edge between two nodes is further constrained by a predefined maximum allowed horizontal distance ( $\Delta x$ ) and a maximum allowed vertical distance ( $\Delta y$ ). These constraints significantly prune the graph at the cost of potentially making no valid path present. Each valid edge is assigned a cost according to  $c(u, v) = \Delta x + 100 \cdot (\Delta y - 1)$ . This cost function penalizes large horizontal deviations and non-uniform vertical spacing, thereby encouraging smooth and consistent paths through the point cloud. The implementation uses NetworkX [80].

<sup>4</sup>[https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.find\\_peaks.html](https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.find_peaks.html)

#### 4.5.3. 1D K-MEANS

The one-dimensional  $k$ -means algorithm is an unsupervised clustering method that partitions a set of scalar values into  $k$  distinct clusters by minimizing the within-cluster sum of squares. The algorithm initially assigns  $k$  predefined cluster centroids and iteratively updates them by alternating between two steps: assigning each value to the nearest centroid and then recomputing each centroid as the mean of all values assigned to it.

#### 4.5.4. A\* PATH FINDING

Given a directed weighted graph with designated start and end nodes, the shortest path between those points is computed using the A\* algorithm (NetworkX<sup>5</sup> [80]) giving a path. It combines the advantages of uniform-cost search and heuristic-guided search. The heuristic function used is  $h(u, v) = |x_v - x_u|$ , where  $x_u$  and  $x_v$  denote the  $x$ -coordinates of nodes  $u$  and  $v$ , respectively. This heuristic encourages paths that remain horizontally consistent, which aligns with the expected geometry of the laser line. The output of the algorithm is an ordered list of nodes representing the optimal path through the graph.

### 4.6. POINT CLOUD PREPROCESSING

The 3D point clouds following from LPP consist mostly out of regular circular pipe wall. To reduce processing time and improve robustness the point clouds are split into defects and pipe wall using a 1D operation from residuals and the remaining points are scaled. See Figure 4.10 for a visual overview.

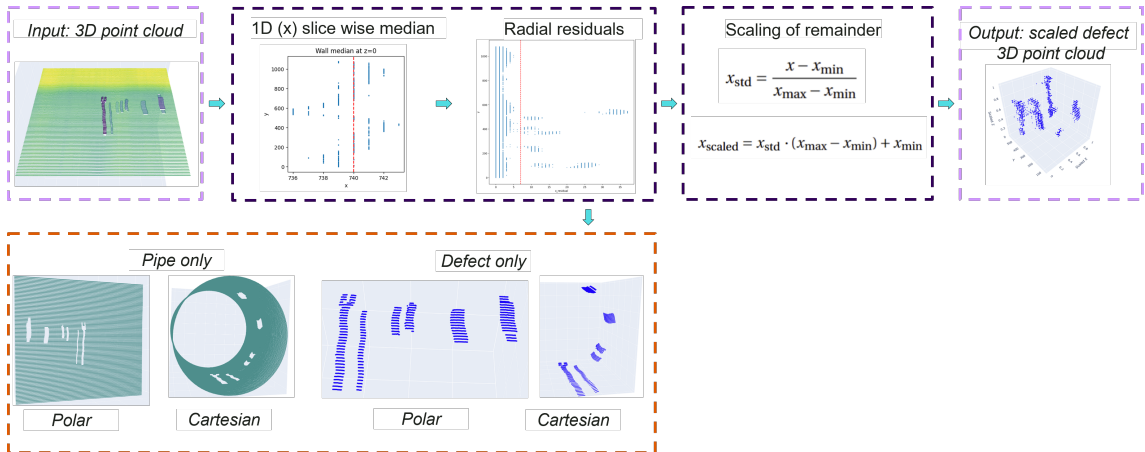


Figure 4.10: Point cloud preprocessing pipeline. Lavender: inputs/outputs; purple: processing steps; turquoise: intermediate results; orange: temporary results.

<sup>5</sup>[https://networkx.org/documentation/stable/\\_modules/networkx/algorithms/shortest\\_paths/astar.html](https://networkx.org/documentation/stable/_modules/networkx/algorithms/shortest_paths/astar.html)



#### 4.6.1. RESIDUAL COMPUTATION

Inspired by the main cluster extraction [21] a simple 1D method of pipe wall extraction was used. For each slice in the point cloud the median radial value is calculated, due to the vast majority of points being part of the pipe wall this median is an estimate of the pipewall, using that median residual radial values are computed which then are used to split data into pipewall (low residual value) and non pipe wall.

#### 4.6.2. MINMAXSCALER

The *MinMaxScaler*<sup>6</sup> performs a linear rescaling of each feature to a specified interval, by default [0, 1], with the goal of preserving relative distances while absolute values are in the same scale. For a given feature, let  $x_{\min}$  and  $x_{\max}$  denote the minimum and maximum observed values. The scaler first computes a standardized value using Equation 4.4a and then maps this value to the target range [min, max] using Equation 4.4b.

$$x_{\text{std}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (a) \quad x_{\text{scaled}} = x_{\text{std}} \cdot (x_{\max} - x_{\min}) + x_{\min} \quad (b) \quad (4.4)$$

### 4.7. SEGMENTATION

In order to automatically find defects the points clouds are segmented using unsupervised clustering algorithms. Two algorithms are compared in this work, *DBSCAN* (used by [21, 22]) and *Torque Clustering (TC)*. *TC* consists of building a merge graph and pruning abnormal mergers and halo mergers. The pipeline for *TC* is visualized in Figure 4.11.

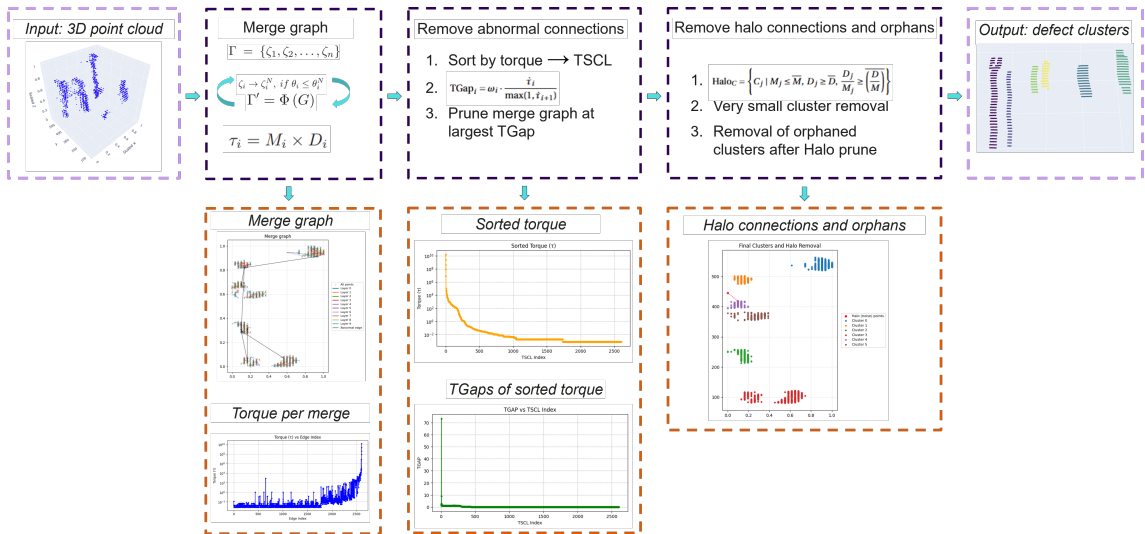


Figure 4.11: *TC* 3D point cloud processing overview. Lavender: inputs/outputs; purple: processing steps; turquoise: intermediate results; orange: temporary results.

<sup>6</sup><https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.MinMaxScaler.html>



#### 4.7.1. DENSITY-BASED SPATIAL CLUSTERING OF APPLICATIONS WITH NOISE

**DBSCAN** [81] is an unsupervised clustering algorithm that groups data points based on density. In contrast to centroid-based methods such as  $k$ -means (see Subsection 4.5.3), **DBSCAN** does not require a predefined cluster count and can identify clusters of arbitrary shape while explicitly labeling noise points. The scikit-learn implementation was used <sup>7</sup>.

#### 4.7.2. TORQUE CLUSTERING

**TC** is an bottom-up hierarchy clustering method that merges clusters based on their mass and mutual proximity [82]. **TC** introduces a constrained merging rule that incorporates cluster mass, nearest-neighbor relationships and a global pruning strategy based on abnormal merger detection [82]. Because the original **TC** code is obfuscated<sup>8</sup>, although an unofficial Python version exists<sup>9</sup> a custom implementation is made with differences discussed.

##### INITIALIZATION AND CLUSTER CONNECTIONS

Let the dataset be denoted in Equation 4.5a with each data point as an individual cluster giving the initial cluster in Equation 4.5b with with corresponding cluster masses in Equation 4.5c.

$$X = \{x_1, \dots, x_n\}, x_i \in \mathbb{R}^D \quad (a) \quad \Gamma^{(0)} = \{\zeta_1, \dots, \zeta_n\} \quad (b) \quad \theta_i = 1, \forall i \in \{1, \dots, n\} \quad (c) \quad (4.5)$$

A graph of mergers  $G$  is built iteratively until a single cluster remains. At each iteration every cluster  $\zeta_i$  is connected to its nearest neighbor  $\zeta_i^N$  with the constraint that the neighbor has a greater than or equal mass following Equation 4.6a.  $\zeta_i^N$  denotes the nearest cluster to  $\zeta_i$  in terms of inter-cluster distance which originally used full pairwise candidate clusters distances [82] but in this work these are restricted to the  $k$  nearest neighbor candidate clusters. Each such directed assignment defines a connection  $C_i$ . Each node is a cluster and edges represent mergers which are connected in  $G$  forming larger clusters as described in Equation 4.6b where  $\Phi(G)$  maps connected components to new clusters. The iterations are shown in Figure 4.12.

$$\zeta_i \rightarrow \zeta_i^N \quad \text{if} \quad \theta_i \leq \theta_i^N \quad (a) \quad \Gamma^{(t+1)} = \Phi(G^{(t)}) \quad (b) \quad (4.6)$$

Each connection  $C_i$  between a cluster  $\zeta_i$  and its nearest neighbor  $\zeta_i^N$  has two properties. The first is the product of their masses as denoted in Equation 4.7a and the second is the squared inter-cluster distance where the distance between two clusters is defined as the minimum distance between any two points belonging to the respective clusters as denoted in Equation 4.7b. Based on these quantities, the torque of a connection is defined as defined in Equation 4.7c.

$$M_i = \theta_i \cdot \theta_i^N \quad (a) \quad D_i = d^2(\zeta_i, \zeta_i^N) \quad (b) \quad \tau_i = M_i \cdot D_i \quad (c) \quad (4.7)$$

<sup>7</sup><https://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html>

<sup>8</sup><https://github.com/JieYangBruce/TorqueClustering>

<sup>9</sup><https://github.com/Cognet-74/TorqueClusteringPy>

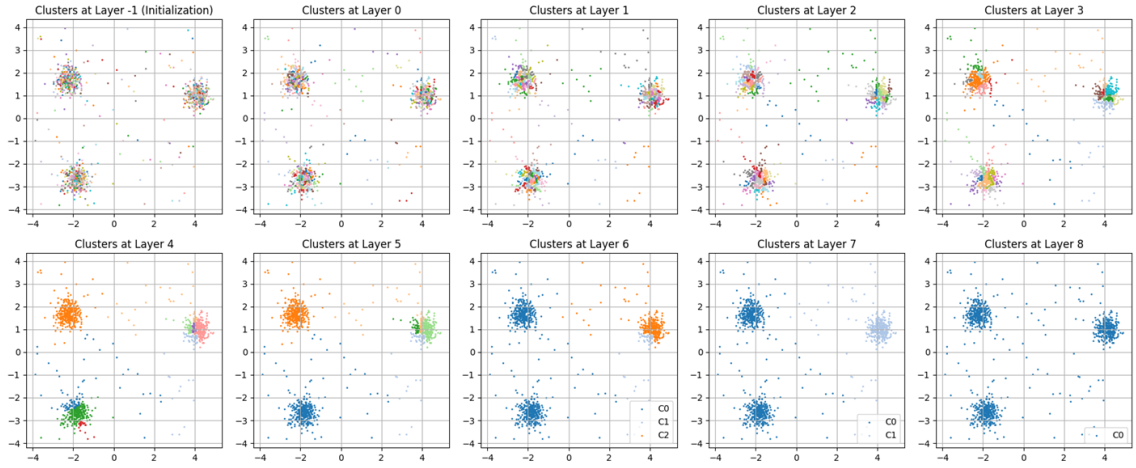


Figure 4.12: Graph construction over every iteration. *Note that Layer -1 is  $\Gamma^{(0)}$*

#### REMOVING ABNORMAL CONNECTIONS

All connections and their torques (see Figure 4.13) are sorted in descending order of  $\tau_i$  to form the **Torque Sorted Connections List (TSCL)** denoted by  $\{\dot{C}_1, \dot{C}_2, \dots, \dot{C}_m\}$  as shown in Figure 4.14. To identify abnormal mergers, the *Torque Gap* is calculated between successive connections present in the TSCL using the formula defined in Equation 4.8a with  $\omega_i$  as a weighting term (see Equation 4.8b) that represents the proportion of high-significance connections among the top  $i$  connections. To prevent exploding gradients between torques a max term was added.

$$TGap_i = \omega_i \cdot \frac{\dot{\tau}_i}{\max(1, \dot{\tau}_{i+1})} \quad (a) \quad \omega_i = \frac{|\text{Large}_C \cap \text{Top}_{C_i}|}{|\text{Large}_C|} \quad (b) \quad (4.8)$$

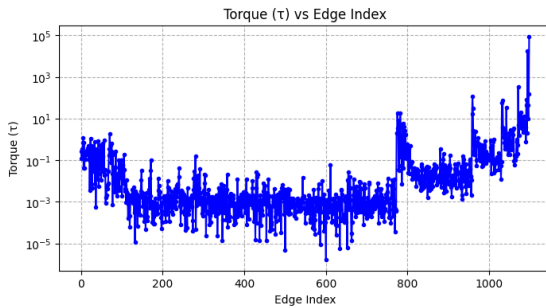


Figure 4.13: Computed torque per edge index.

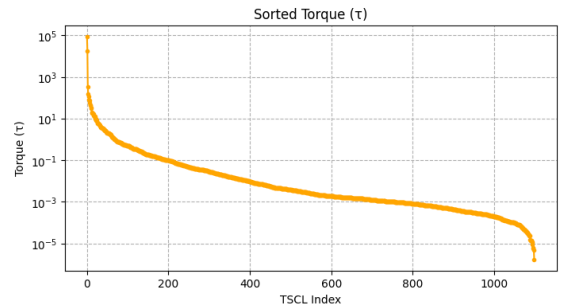


Figure 4.14: TSCL graph showing sorted torque.

The first step in computing the *TGap* is to define the set of large connections, see Equation 4.9a where  $\bar{\tau}$ ,  $\bar{M}$  and  $\bar{D}$  are the global means of  $\tau$ ,  $M$  and  $D$  respectively. The set of top- $i$  connections is defined in Equation 4.9b. Using Equation 4.8b  $\omega_i$  is computed at each point in the TSCL as shown in Figure 4.15.

$$\text{Large}_C = \left\{ C_j \mid \tau_j \geq \bar{\tau}, M_j \geq \bar{M}, D_j \geq \bar{D} \right\} \quad (a) \quad \text{Top}_{C_i} = \{\dot{C}_1, \dot{C}_2, \dots, \dot{C}_i\} \quad (b) \quad (4.9)$$

The index corresponding to the largest Torque Gap, see Equation 4.10, defines the number of abnormal connections. The top  $L$  connections in the TSCL are then removed from the graph. The connected components of the remaining graph define the main cluster partition as shown in Figure 4.16 which results in 3 clusters for the synthetic data used here as the last two mergers (black lines) are removed.

$$L = 1 + \operatorname{argmax}_{i \in \{0, \dots, n-1\}} (\text{TGap}_i) \quad (4.10)$$

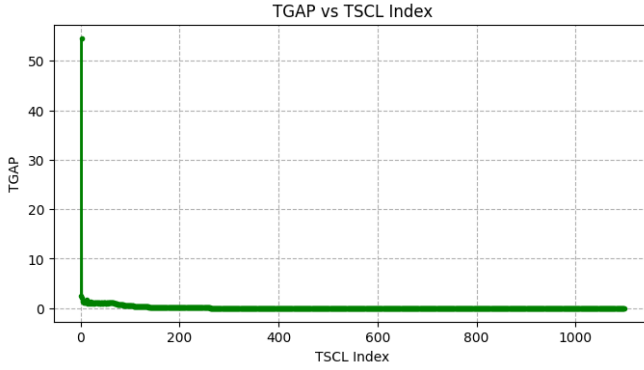


Figure 4.15:  $TGAP$  of all TSCL indices showing  $TGAP$  imbalance.

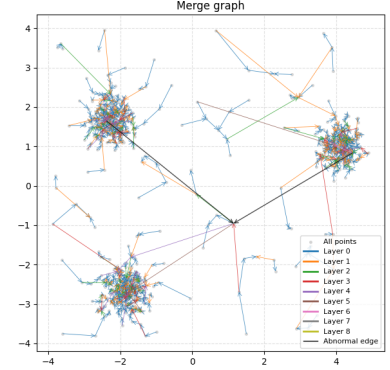


Figure 4.16: Merges visualized.

#### HALO CONNECTIONS AND NOISE IDENTIFICATION

Following the removal of abnormal mergers, additional weak and structurally detached connections are identified as halo connections. These typically correspond to small fragments or isolated points that do not belong to the core of any cluster. The set of halo connections is defined in Equation 4.11 where  $\overline{D/M}$  denotes the mean of  $\frac{D_i}{M_i}$  over all connections. Removing these halo connections from the graph yields small, weakly connected components which are interpreted as noise or outlying fragments. Figure 4.17 showcases the pruning based on this on synthetic data. In the present implementation, additional practical heuristics were applied at this stage to explicitly mark tiny components and detached fragments as noise, ensuring that spurious micro-clusters are not included in the final clustering result.

$$\text{Halo}_C = \left\{ C_j \mid M_j \leq \overline{M}, D_j \geq \overline{D}, \frac{D_j}{M_j} \geq \left( \frac{\overline{D}}{\overline{M}} \right) \right\} \quad (4.11)$$

## 4.8. EVALUATION

This section details the auxiliary methods used for data validation and performance assessment. Morphological operations, including opening, closing<sup>10</sup> and skeletonization [83]<sup>11</sup>, are employed to clean artifacts resulting from the polar transformation of synthetic binary masks.

<sup>10</sup>[https://docs.opencv.org/4.x/d9/d61/tutorial\\_py\\_morphological\\_ops.html](https://docs.opencv.org/4.x/d9/d61/tutorial_py_morphological_ops.html)

<sup>11</sup>[https://docs.opencv.org/4.x/df/d2d/group\\_\\_ximgproc.html#ga37002c6ca80c978edb6ead5d6b39740c](https://docs.opencv.org/4.x/df/d2d/group__ximgproc.html#ga37002c6ca80c978edb6ead5d6b39740c)

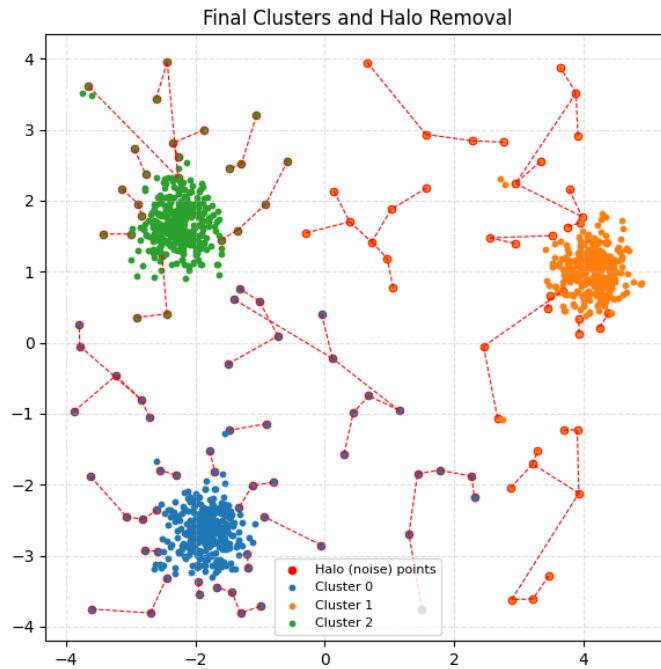


Figure 4.17: Halo removal with additional noise heuristics resulting in the final clusters.

For 3D assessment, [ICP](#) [84] aligns point clouds by minimizing the distance between corresponding points [58], facilitating error computation. Evaluation metrics for these point clouds include [Hausdorff Distance 95th Percentile \(HD95\)](#) and mean point-wise registration error.

The center-finding methodology for circular laser profiles transitioned from the classical [Circular Hough Transform \(CHT\)](#) to a grid-based approach ([Subsection 4.4.2](#)). These methods were evaluated using synthetic images to directly assess center estimation accuracy and computational cost in a controlled environment. While initial visual testing was conducted on the first real dataset, the lack of ground truth coordinates necessitated an indirect performance assessment. This was achieved by measuring [HD95](#) and [Mean Absolute Error \(MAE\)](#) (in pixels) on the resulting quasi-synthetic point clouds.

Finally, the stability of the grid-based approach was verified through a rotation experiment using real images. This involved estimating the center in rotated frames and transforming the coordinates back to the original reference frame to measure variance.

# 5

## RESULTS AND DISCUSSION

This chapter demonstrates the results gathered from the experimental setup and data processing pipeline. It consists of calibration, the acquired data, preprocessing results, laser line extraction, reconstruction results, point cloud preprocessing results and segmentation. The sections discuss the results from the **DMME** process in the development of each method and knowledge gained at each step.

### 5.1. CALIBRATION

A set of planar calibration patterns was generated using the OpenCV pattern generation toolkit<sup>1</sup>. The selected templates included standard checkerboards, Radon checkerboards, symmetric and asymmetric circle grids, and ChArUco boards. Representative examples are shown in [Figure 5.1](#). All patterns were printed and laminated which did introduce slight warping due to shrinkage during cooling. A summary of the number of images and the reprojection error for various patterns is provided in [Table 5.1](#).

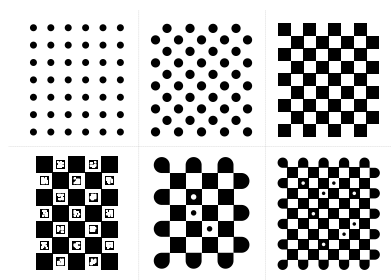


Figure 5.1: Calibration patterns

Table 5.1: Per pattern calibration results.

| Pattern            | N Images | Reprojection Error |
|--------------------|----------|--------------------|
| Checkerboard       | 14       | 1.31px             |
| Radon Checkerboard | 8        | 0.35px             |

Calibration images were acquired using the robot-mounted camera without the protective housing. The native sensor resolution was 4056×3040 however images were downsampled to 1200x1200.

<sup>1</sup>[https://github.com/opencv/opencv/tree/cbf71c380f5e593263ab9bdc9119fb8d81c30de1/doc/pattern\\_tools](https://github.com/opencv/opencv/tree/cbf71c380f5e593263ab9bdc9119fb8d81c30de1/doc/pattern_tools)

After manual selection based on (motion) blur and occlusion calibration was done on each pattern. The reprojection error per used pattern is shown in Table 5.1, differences are mainly the result from lighting conditions and planarity of the patterns. The resulting intrinsic matrix  $K$  and distortion coefficients  $D$  are reported in Table 5.1.

$$K = \begin{bmatrix} 391.47 & 0.70 & 610.94 \\ 0 & 390.72 & 609.97 \\ 0 & 0 & 1 \end{bmatrix} \quad (a) \quad D = \begin{bmatrix} -0.011 & 0.008 & -0.011 & 0.003 \end{bmatrix}^T \quad (b)$$

Coverage plots were generated for each pattern to assess the spatial distribution of detected points. These visualizations are included in Figure 5.2 and Figure 5.3. Pattern types that rely on blob detection or marker detection were more sensitive to small local distortions due to lamination which increased their reprojection errors.

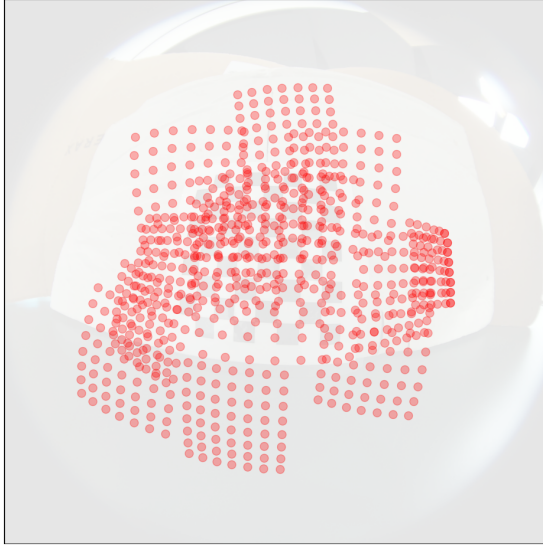


Figure 5.2: Coverage checkerboard.

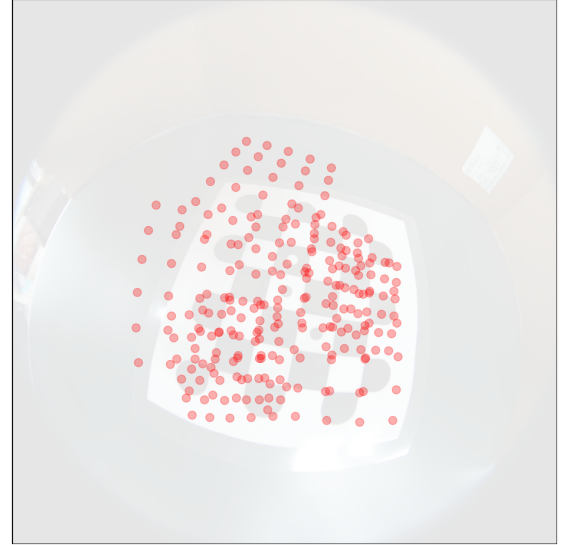


Figure 5.3: Coverage radon checkerboard.

## 5.2. DATA

Data was acquired using the final physical hardware configuration after iterative testing and hardware adjustments based on earlier measurements. Only the final setup per test modality are considered. Various experimental scenarios were evaluated:

Table 5.2: Dataset characteristics.

| Dataset                                                                        | Resolution | N Images |
|--------------------------------------------------------------------------------|------------|----------|
| 300-310mm $\varnothing$ PVC; plastic blocks (Dataset 1)                        | 1080x1080  | 96       |
| 300mm $\varnothing$ PVC; uncoated stainless steel evaluation plate (Dataset 2) | 1200x1200  | 321      |
| 580mm $\varnothing$ PVC; uncoated stainless steel evaluation plate (Dataset 3) | 1200x1200  | 89       |
| Uncoated metal form with significant ovality (Dataset 4)                       | 1200x1200  | 31       |

All datasets consist of images containing a continuous laserline around the pipeline contour. In

addition, secondary reflections are present, especially in [Figure 5.5](#) and [Figure 5.6](#). In the block and evaluation plate defect experiments, the defects are seen as small radial deviations in the laser line. Additionally the laser intensity was increased in [Dataset 2](#) and [Dataset 3](#) which led to thicker laser lines, more saturation and increased indirect reflection intensity from both the uncoated stainless steel and pipewall, plastic remained relatively unaffected. In [Dataset 4](#), which is not quantitatively evaluated, the material leads to strong diffusion as shown in [Figure 5.7](#).

The uncoated evaluation plate exhibits higher reflectivity than the surrounding pipe material. This results in increased illumination of the pipe interior and stronger secondary reflections in the recorded images. Material-dependent reflectance effects are particularly evident in the blue barrel experiments. Compared to the PVC pipe, the barrel produces visibly thicker laser lines on the wall. Differences between the barrel material, the metal evaluation plate, and plastic components on the plate lead to distinct variations in laser line thickness, as illustrated in [Figure 5.6](#). A clear geometric difference between the test cases is also observable. The larger diameter of the blue barrel results in a noticeably different laser line curvature compared to the PVC pipes, as seen when comparing [Figure 5.5](#) and [Figure 5.6](#). These variations in material properties, diameter, defects and laser intensity provide a diverse dataset for evaluating the robustness of subsequent processing and reconstruction steps.



Figure 5.4: Example from [Dataset 1](#)

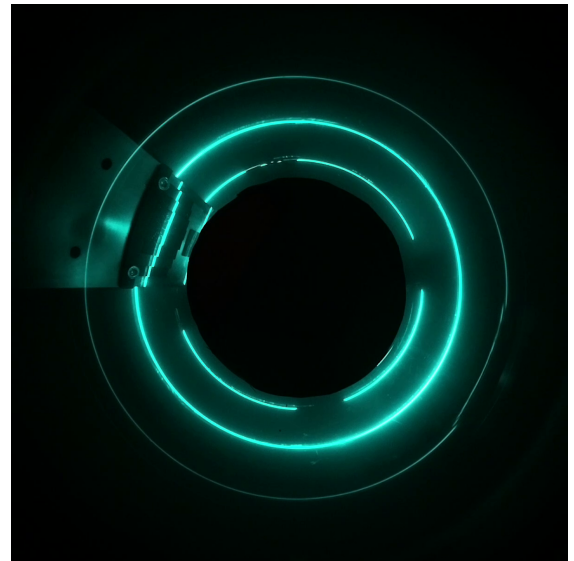
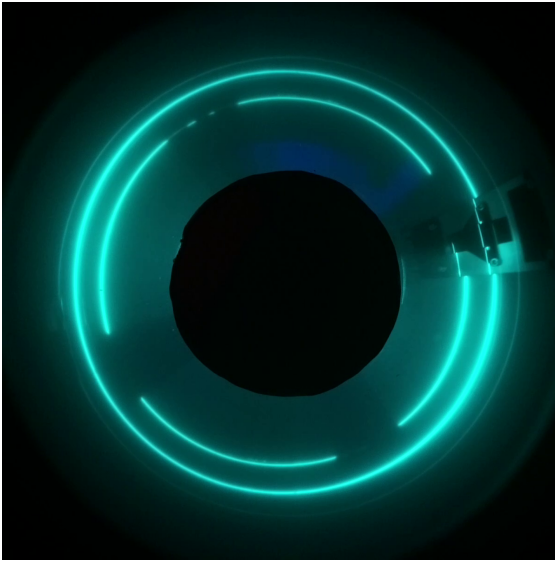
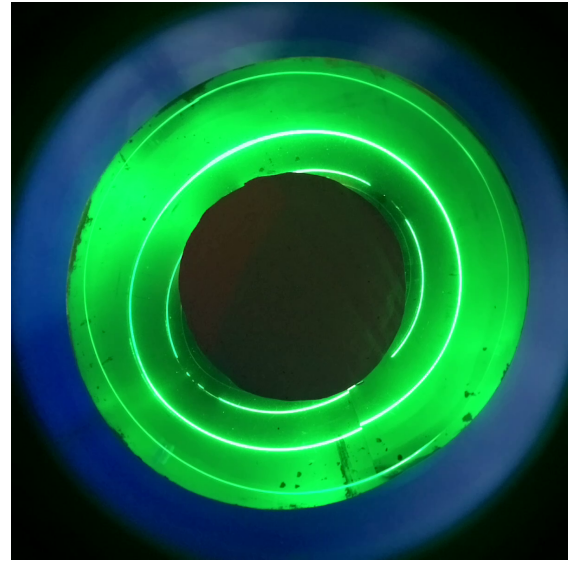


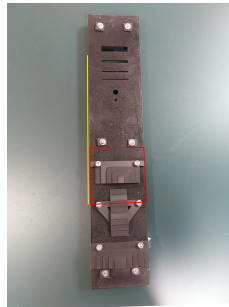
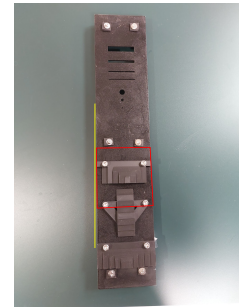
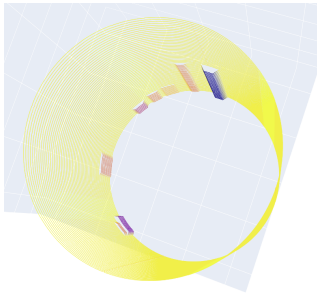
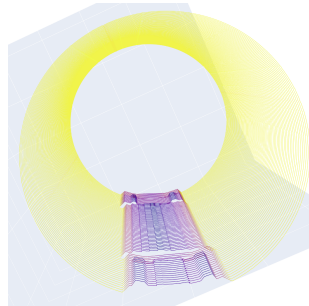
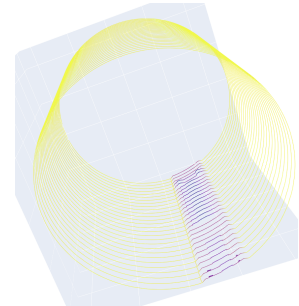
Figure 5.5: Example from [Dataset 2](#)

In [Figures 5.8 to 5.10](#), the longitudinal scan section used for evaluation is highlighted in red, while the full range of motion is shown in yellow. Synthetic data were generated from the pipe's range of motion for each dataset, but evaluation was restricted to regions where the real geometry could be approximated by block-like structures. Based on these regions, quasi-synthetic point clouds were produced, as shown in [Figure 5.11 to 5.13](#). For each dataset, a quasi-synthetic point cloud was constructed by combining real defect measurements with their corresponding point cloud points to enable px to mm conversions, yielding a ground truth dataset for evaluation. Full geometric comparisons were not performed, as



Figure 5.6: Example from [Dataset 3](#)Figure 5.7: Example from [Dataset 4](#)

the synthetic point cloud generation was limited to simple radial defects; consequently, quasi-synthetic point clouds were made for the block and staircase sections of the evaluation plate.

Figure 5.8: Range in [Dataset 1](#)Figure 5.9: Range in [Dataset 2](#)Figure 5.10: range in [Dataset 3](#)Figure 5.11: Evaluation [Dataset 1](#).Figure 5.12: Evaluation [Dataset 2](#).Figure 5.13: Evaluation [Dataset 3](#).



### 5.3. IMAGE PREPROCESSING

Image preprocessing reduces noise and stabilizes the downstream laser line extraction and reconstruction stages. An edge preserving filter [78] was used to suppress noise and reduce the effect of partial or inconsistent low intensity reflections while maintaining sharp laser line boundaries. This proved particularly important for the datasets described in Section 5.2, where reflective surfaces(uncoated evaluation plate) introduce strong secondary reflections. Following filtering, each image was transformed into polar coordinates. This transformation requires accurate estimation of the pipe center and therefore constitutes a critical preprocessing step.

Initially the classical CHT was used to find the laser profile center. However, the adjusted grid based concentric circle center estimation method [79] was significantly faster and more robust. This follows from experiments on 120 synthetic images with known pixel-wise ground truth center coordinates. For this synthetic benchmark, the grid based method achieved a MAE of 0.63 px, compared to 2.51 px for CHT for the detected pixel wise centers. It reduced the per-frame processing time from 0.22 s to 0.04 s. These results indicate both higher accuracy and substantially improved efficiency for the grid based approach under idealized conditions. The methods were subsequently evaluated ground truth data derived from the Dataset 1 setup. Consistent with the synthetic experiments, the grid based method produced lower errors. In the Dataset 1, the mean point-wise registration error and HD95 respectively decreased from 1.79 px and 3.13 px when using CHT to 1.09 px and 2.50 px with the grid based method. Qualitative visual inspection further showed that the grid based approach is less sensitive to secondary laser line reflections and deformations present in the real data. A remaining limitation of the grid based method is its reduced robustness in cases of strong partial occlusion of the true laser lines, for example when not all laserlines are visible in over the whole image due to robot pitch or yaw. The combination of improved accuracy, lower sensitivity to reflections, and significantly reduced computational cost led to the CHT being discarded after Dataset 1 in favor of the grid based center estimation approach.

A final stability experiment was conducted on real images. The results showed that rotation and the associated inverse translations have a negligible effect on center estimation. The average pixel-wise distance between centers before and after rotation was 0.50 px, attributable primarily to translation effects, even for the noisiest  $1200 \times 1200$  images from Dataset 3. This demonstrates that the center estimation process is relatively stable with respect to image rotation and coordinate transformations as would be expected from rotating circles. The method also demonstrated strong performance based on visual evaluation in Dataset 4, where the laser profile exhibits an oval geometry.

### 5.4. LASER LINE EXTRACTION

Laser line extraction was formulated as a 1D row wise signal analysis problem in the polar image domain. For each image row, candidate laser points were obtained by detecting local intensity maxima. A faster signal extraction method, previously used during circle center estimation

for 1D row wise peak detection, was also evaluated. Although computationally efficient, it was more sensitive to noise in the polar domain and was therefore not adopted for the final pipeline.

The extracted candidate points were subsequently grouped into candidate laserlines using graph based path finding. An initial implementation based on Dijkstra's algorithm was found to be computationally expensive. Replacing it with A\* search, combined with an admissible heuristic, reduced computation time substantially while preserving path quality. Further analysis showed that constructing a fully connected density graph was unnecessary. Instead, a sparse graph was constructed by limiting outgoing edges per node using Pareto dominance criteria and by capping connections to nearest neighbors (in the polar domain). This reduced graph density without affecting the resulting laser paths, as illustrated in Figure 5.14 and Figure 5.15. Graph construction and path finding time decreased from 1.45 s per image to 0.14 s per image solely due to sparsification on the graph in real data from Dataset 1 after which it was adopted.

Laser line extraction remains one of the most time intensive stages of the processing pipeline. While the path finding approach is effective at enforcing global continuity and rejecting outliers, it introduces a smoothing effect. As a result, small scale radial deviations, such as shallow defect staircases of approximately 1 mm present in Dataset 2 and Dataset 3, may be partially smoothed. This trade off between robustness and sensitivity is considered acceptable for the targeted defect scales in the evaluated datasets.

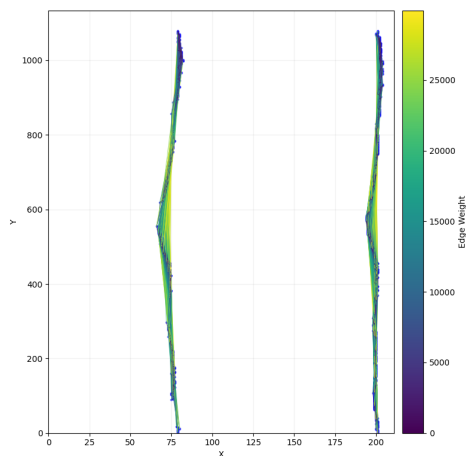


Figure 5.14: Dense graph of candidate points in polar coordinates from an image from Dataset 1.

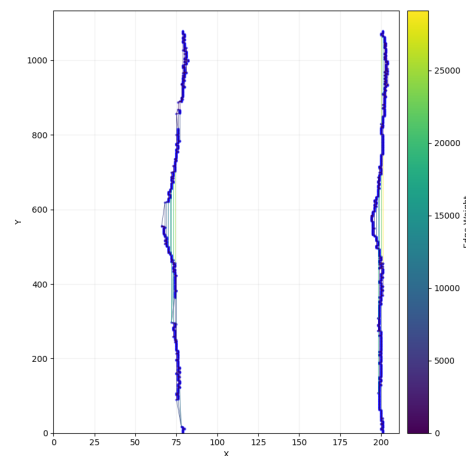


Figure 5.15: Sparse graph of candidate points in polar coordinates from an image from Dataset 1.

## 5.5. RECONSTRUCTIONS

By stacking the per frame point clouds along the longitudinal axis, full 3D reconstructions of the pipe interior were obtained for all datasets (see Figure 5.19 to Figure 5.23). Overall, the reconstructed geometry captures the pipe profile reliably and all block type defects are clearly visible, as illustrated for Dataset 1 in Figure 5.19. Small scale structures such as 1 mm staircases, small holes and even the screws used to mount the evaluation plate are visible, as shown in Figure 5.16.

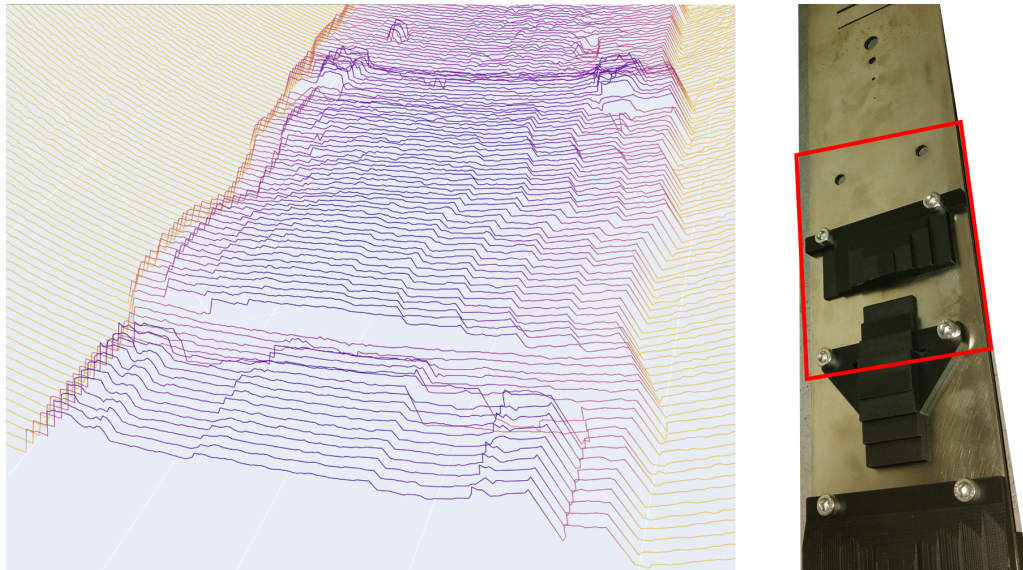


Figure 5.16: Defects in the 3D reconstruction and the shown region of the evaluation plate.

In addition to the artificial defects, a non intentional deformation caused by external pressure on the PVC pipe was detected, see [Figure 5.17](#). This deformation originated from the wooden stabilization blocks used during testing and demonstrates the sensitivity of the reconstruction to real geometric deviations.

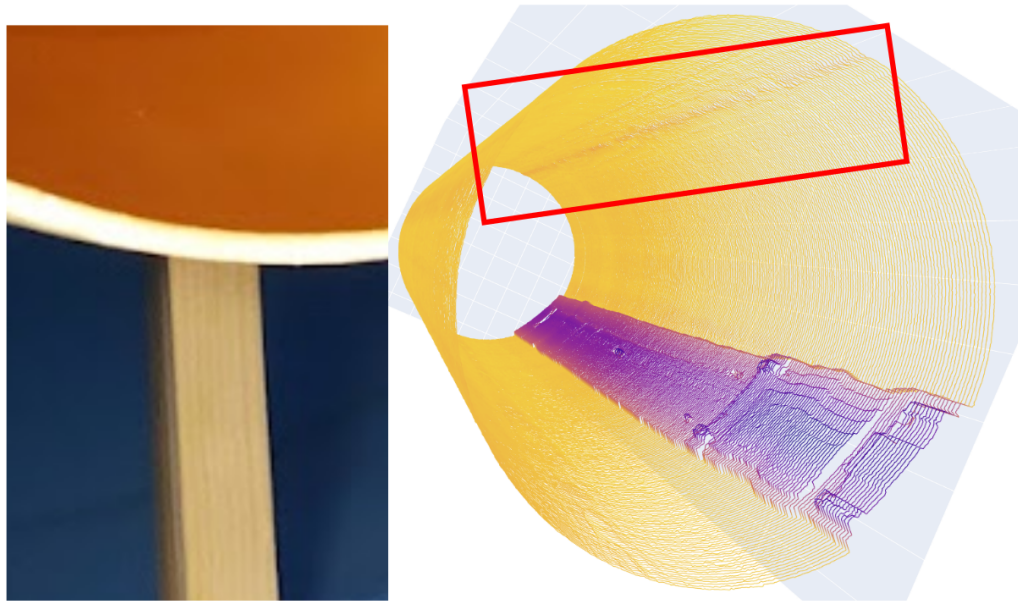


Figure 5.17: Externally induced stress due to wooden blocks visible in the 3D reconstruction.

Not all defect types were reconstructed equally well. Negative radius features such as holes and slits were inconsistently captured, particularly in the uncoated PVC evaluation pipe. Strong laser reflections on the pipe wall and within the cavities led to outlier points on both sides of the true surface. The A\* algorithm favors a continuous path which results in lasers forming a flip from negative to positive radial geometry in the 3D reconstruction. This is shown in [Figure 5.18](#).

These effects limited the visibility and geometric accuracy of such defects in the final point clouds.

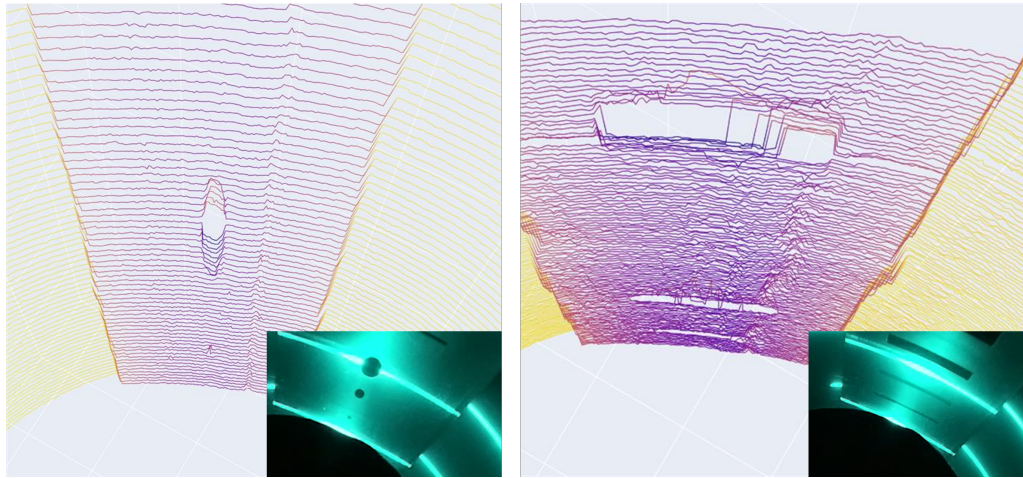


Figure 5.18: Holes and slits form radial flip geometry in the 3D reconstruction.

Quantitative evaluation was conducted using the quasi-synthetic point clouds described in [Section 5.2](#), with the resulting mean point-wise registration error and [HD95](#) summarized in [Table 5.3](#). Across all datasets, the metrics indicate sub millimeter to low millimeter reconstruction accuracy. For [Dataset 1](#) and [Dataset 2](#), which were acquired at shorter sensor distances, the mean point-wise registration error remains below 1 mm and [HD95](#) below 2 mm, confirming stable reconstruction of the pipe wall and block type, positive radius defects. In [Dataset 3](#), the larger pipe diameter and increased sensor distance lead to higher mean point-wise registration error, while [HD95](#) remains comparable or slightly lower than in [Dataset 2](#). This behavior reflects reduced pixel wise deviations of the evaluation plate and a smoothed overall reconstruction at larger diameters which highlights the impact of reduced spatial resolution.

The mean point-wise registration error primarily captures global geometric consistency and is dominated by the reconstructed pipe wall, which lowers the overall error by outweighing localized deviations. In contrast, [HD95](#) is more sensitive to local outliers caused by defects, strong reflections, and approximations in the quasi-synthetic evaluation data. These metrics show that block like and positive radius defects are reconstructed reliably while negative radius features and non modeled irregularities remain the dominant contributors to residual error due to the large jump in [HD95](#) between the datasets. Overall, the results in [Table 5.3](#), supported by the qualitative reconstructions from [Dataset 1](#) to [Dataset 3](#), demonstrate that the proposed pipeline is suitable for millimeter scale defect detection under the tested conditions, while clearly exposing its current limitations related to reflectance effects, distance dependent resolution and material changes.

The accuracy of the evaluation is further constrained by the limitations of the quasi-synthetic reference data. Non regular defects, such as the small deformation from the external stress observed in [Dataset 2](#), are not included in the synthetic models and pitch, yaw and roll intro-



Table 5.3: Point Cloud geometric evaluation through real measurement based quasi-synthetic point clouds.

| Dataset   | mean point-wise registration error | HD95              | N Evaluation Frames |
|-----------|------------------------------------|-------------------|---------------------|
| Dataset 1 | 1.0843px ; 0.43mm                  | 2.5000px ; 0.99mm | 57                  |
| Dataset 2 | 1.2876px ; 0.64mm                  | 3.9051px ; 1.94mm | 78                  |
| Dataset 3 | 2.0774px ; 1.79mm                  | 3.6401px ; 3.15mm | 28                  |

duced further deviation. In addition, screws and other non block elements on the evaluation plate (Dataset 1 and Dataset 2) were only approximated, which introduces modeling error into the reference point clouds and affects the reported metrics.

The visualizations provide additional insight into the reconstruction quality and the current limitations. The Cartesian and polar views in Figure 5.19 and Figure 5.20 highlight the block defects and the diameter variation in Dataset 1 (orange is 300  $\varnothing$  while yellow is 310mm  $\varnothing$ ). For Dataset 2, the evaluation plate with staircases, screws, holes and slits is visible in Figure 5.21 and Figure 5.22, including the externally induces stress. In Dataset 3, shown in Figure 5.23 and Figure 5.24 the reduced resolution is visible due to the increased noisy in the profile and the evaluation plate appears smoother and less pronounced due to the increased distance from the camera, which reduces spatial resolution.

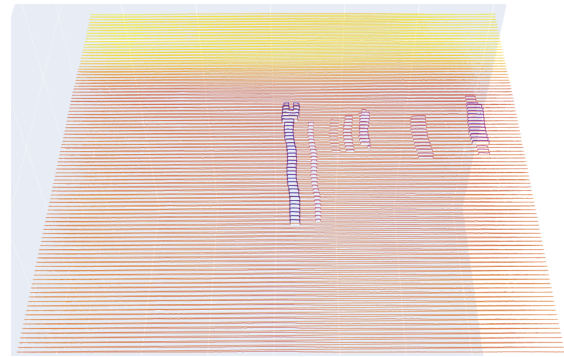
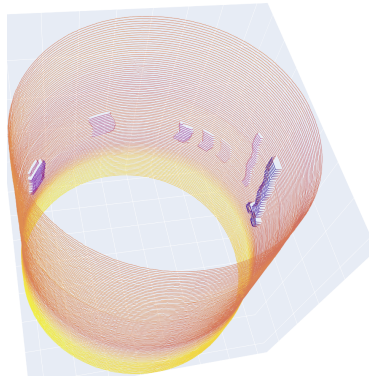


Figure 5.19: Cartesian 3D reconstruction of Dataset 1.

Figure 5.20: Polar 3D reconstruction of Dataset 1.

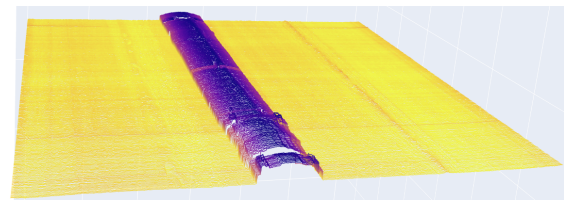
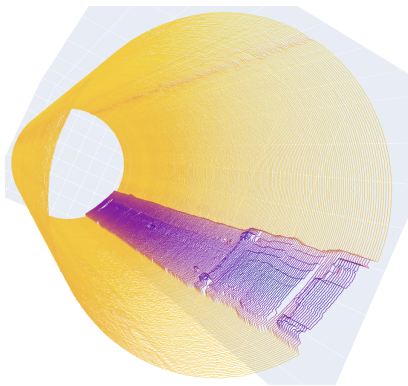


Figure 5.21: Cartesian 3D reconstruction of Dataset 2.

Figure 5.22: Polar 3D reconstruction of Dataset 2.

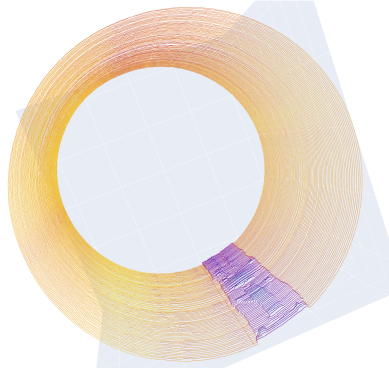


Figure 5.23: Cartesian 3D reconstruction of Dataset 3.

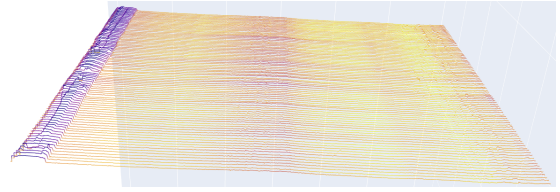


Figure 5.24: Polar 3D reconstruction of Dataset 3.

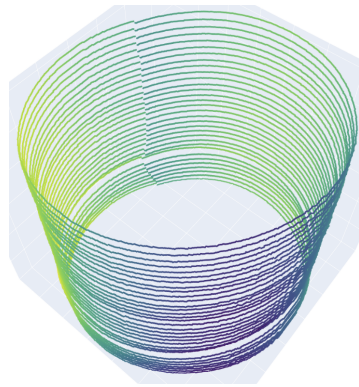


Figure 5.25: Cartesian 3D reconstruction of Dataset 4.

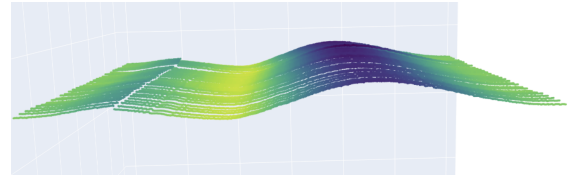


Figure 5.26: Polar 3D reconstruction of Dataset 4.

## 5.6. 3D POINT CLOUD PREPROCESSING

Point cloud preprocessing is applied on a layer by layer basis. For each slice, the global radial median is computed to approximate the local pipe wall, as shown in Figure 5.27. Radial residuals relative to this median are then thresholded to separate wall and non wall points, illustrated in Figure 5.28. This step removes the dominant wall structure and substantially reduces the computational effort required for subsequent clustering.

The remaining non wall points are finally scaled in the radial direction, as shown in Figure 5.29, to normalize deviations across different pipe diameters. This preprocessing stage effectively isolates defect related geometry while preserving the relevant spatial characteristics.

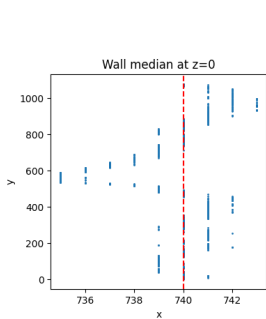


Figure 5.27: Median of slice.

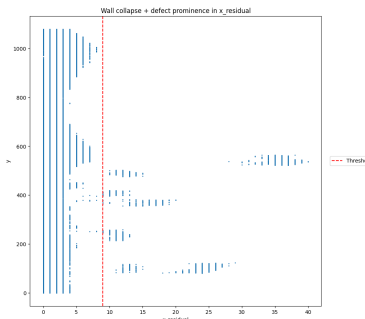


Figure 5.28: Wall residuals of slice

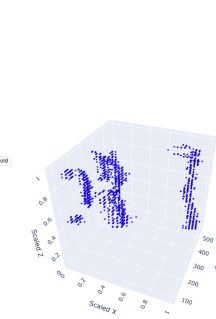


Figure 5.29: Scaled non-wall points.

### 5.7. SEGMENTATION

Segmentation was done using two unsupervised clustering approaches, **DBSCAN** and **TC**. Only **Dataset 1** contains multiple clearly spatially disconnected defects making it the primary dataset for qualitative assessment of clustering behavior. In **Dataset 2** and **Dataset 3**, defects are connected as they're all attached to the evaluation plate, such that clustering results in a single dominant cluster or artificial splits within it. Consequently, visual analysis focuses on **Dataset 1**, while the larger datasets are mainly used to assess noise suppression behavior and processing time.

Overall, **DBSCAN** proved to be significantly faster than **TC**, with detailed performance metrics discussed in [Section 5.8](#). In [Figure 5.30](#) separation can be observed with some mislabeling in defects close on the scaled y axis ( $\phi_s$ ). In contrast, **TC** becomes unstable due to the halo removal separating different sections of longer and thinner defects in **Dataset 1** into noise, as the relative distances between defect points remain small. The behavior of **TC** is strongly influenced by feature scaling, a better result was obtain in [Figure 5.32](#). Best results were obtained when the y values ( $\phi$ ) were left unscaled, while radial and longitudinal dimensions were still normalized. This reflects the fact that  $\phi$  spans a fixed range based on the image size (due to linear scaled polar transform), whereas the radial and longitudinal coordinates vary substantially and encode more discriminative geometric information. In contrast, **DBSCAN** requires all dimensions to be expressed in a comparable scale to produce meaningful density estimates.

From a computational perspective, **TC** exhibits inefficiencies in the initial merging layers, which dominate runtime and limit scalability. This makes **TC** less suitable for large point clouds with extended longitudinal defects, where many early merge operations are required. Conversely, **DBSCAN** struggles primarily with defects that are spatially close but should remain distinct, while handling elongated structures more robustly. The qualitative differences between the segmentation approaches are illustrated in [Figure 5.30](#) to [Figure 5.32](#). **DBSCAN** is better suited for large scale processing than this study's implementation of **TC**.

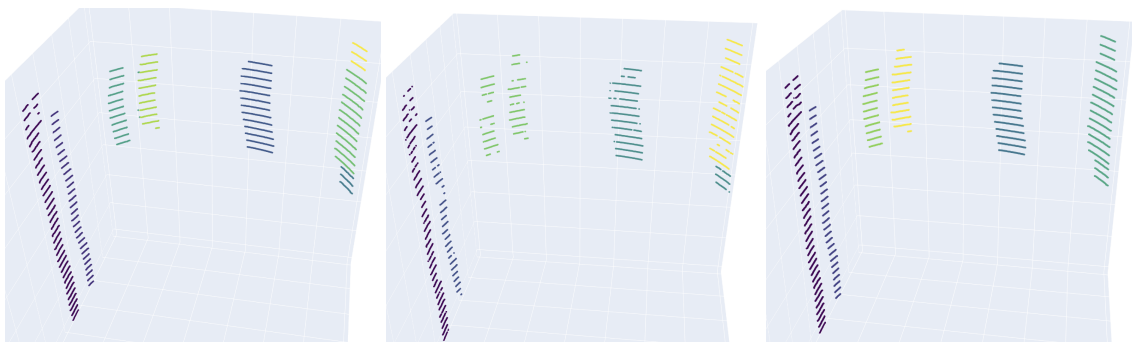


Figure 5.30: **DBSCAN** segmentation in Cartesian space.

Figure 5.31: **TC** with scaled angular component.

Figure 5.32: **TC** with unscaled angular component.

#### EXPLODING TGAP PROBLEM

One issue found with the formulas in the original **TC** paper [82] were unstable *TGAPs*. The *TGAP* formula had the limitation that extremely small values of  $\hat{r}_{i+1}$  can lead to instability when com-



puting *TGAPs*. To prevent a divergence shown in Equation 5.1a the denominator is bounded below by one as shown in Equation 5.1b. An example with synthetic data showcases the instability in Figure 5.33 which leads to no very early merger pruning as super small mergers create a large *TGAP*. Adjusting the *TGAP* function using Equation 5.1b leads to a much stabler *TGAPs* as shown in Figure 5.34.

$$\lim_{\dot{\tau}_{i+1} \rightarrow 0^+} \frac{\dot{\tau}_i}{\dot{\tau}_{i+1}} = \infty \quad (a) \quad TGap_i = \omega_i \cdot \frac{\dot{\tau}_i}{\max(1, \dot{\tau}_{i+1})} \quad (b) \quad (5.1)$$

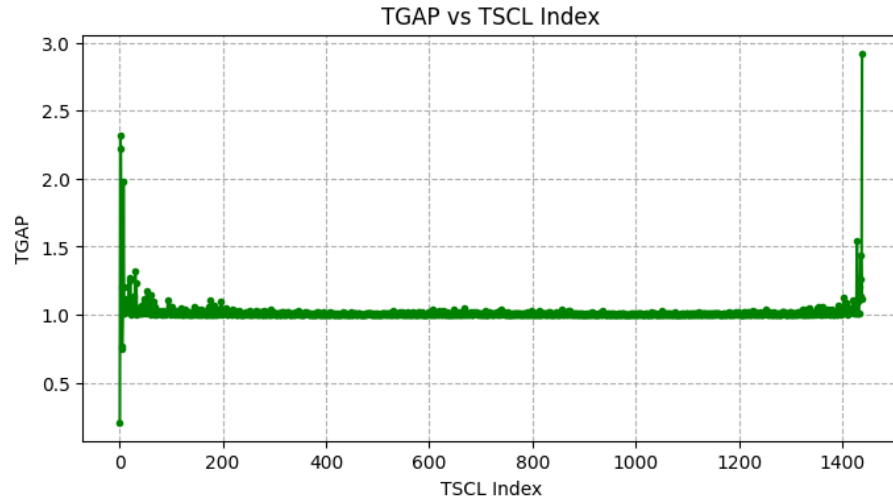


Figure 5.33: *TGAPs* of all TSCL indices.

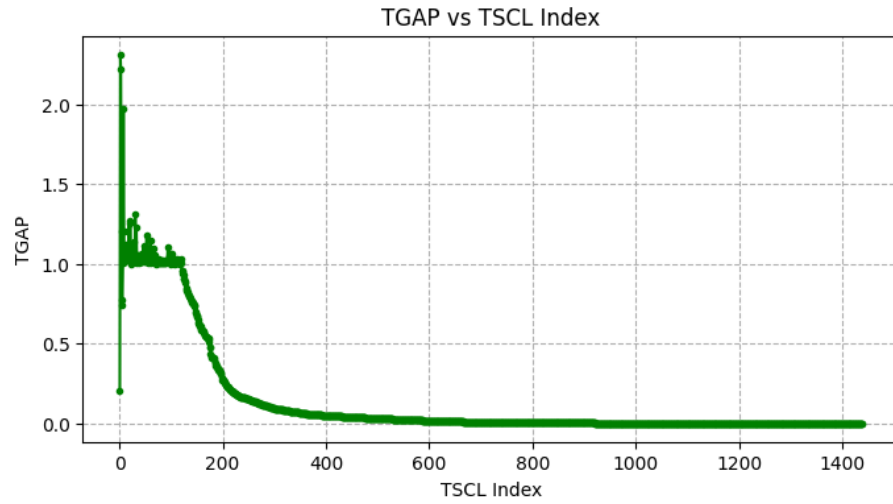


Figure 5.34: Corrected *TGAPs*.

### 5.8. PERFORMANCE

The average computational performance per image or layer for the main processing stages is summarized in Table 5.4. The reported times reflect end to end execution on the final datasets and are averaged over all processed frames or slices.

Image preprocessing shows comparable runtimes across all datasets, ranging from 0.22 s to 0.31 s per image. The slightly higher cost observed for Dataset 2 is attributed to the larger number of evaluation frames and increased image resolution. Laser line extraction exhibits similar behavior, with processing times between 0.16 s and 0.20 s per image, confirming that this stage remains one of the dominant contributors to overall runtime regardless of dataset characteristics.

The largest performance differences are observed in the segmentation stage. This study's implementation of TC scales poorly with dataset size and extended defects, which is most likely due implementation of the merge graph. In Dataset 1 the results show relatively low average clustering time due to the presence of only a few small, disconnected defects. The other datasets on the other hand contain the evaluation plate which is a large connected defect region (large amount of points) which results in substantial increases in processing time for Dataset 2 and Dataset 3 with an average of 1.20 s and 0.22 s per layer respectively. In contrast, DBSCAN consistently achieves near negligible run times across all datasets, remaining below 0.01 s per layer even for the larger point clouds.

Overall, the results in Table 5.4 demonstrate that laser line extraction and preprocessing dominate the computational budget, while DBSCAN provides a scalable and efficient segmentation alternative. Although TC can yield finer segmentation in certain scenarios, its computational cost limits its applicability for larger datasets or real time operation.

Table 5.4: Per image/layer averages.

| Dataset   | Img. Pre. (s) | Laser extraction (s) | Point cloud Pre. (s) | TC (s) | DBSCAN (s) |
|-----------|---------------|----------------------|----------------------|--------|------------|
| Dataset 1 | 0.22          | 0.16                 | 0.00                 | 0.05   | 0.00       |
| Dataset 2 | 0.31          | 0.20                 | 0.00                 | 1.20   | 0.00       |
| Dataset 3 | 0.28          | 0.19                 | 0.00                 | 0.22   | 0.01       |

# 6

## CONCLUSION AND DISCUSSION

This chapter concludes the main findings of the thesis, reflects on the research questions and results, and discusses the practical and scientific contributions, limitations, and directions for future research.

### 6.1. CONCLUSION

This thesis investigated how **LPP** can be applied to enable 3D reconstruction and unsupervised segmentation for defect identification in drinking water pipelines:

*How can laser projection profilometry be applied to enable 3D reconstruction and unsupervised segmentation for defect identification in drinking water pipelines?*

The work addressed the full processing chain, from data acquisition and calibration, image preprocessing to reconstruction, preprocessing, segmentation, and evaluation. The results demonstrate that **LPP** is a viable sensing modality for capturing millimeter scale geometric deviations in controlled pipeline environments, while also revealing clear limitations related to reflectance, material properties, and orientation of the robot. The sub-questions are answered in the rest of this section.

RQ1: *How can accurate 3D reconstruction be achieved from **LPP** data in drinking water pipelines?*

1. *What calibrations are required to compensate for distortion?*
2. *How can the acquisition system and data processing be optimized for noisy conditions?*

Regarding the first research question, accurate 3D reconstruction from **LPP** data was achieved through image preprocessing and laser line extraction. The adoption of a grid-based circle center estimation method significantly improved both accuracy and computational efficiency compared to a classical **CHT** based approach. This step proved critical for stabilizing the polar

transformation and, consequently, the reconstruction quality. Across all datasets, the resulting reconstructions captured the global pipe geometry reliably and resolved positive radius defects at sub millimeter to low millimeter accuracy. However, negative radius features such as holes and slits were reconstructed less consistently due to strong secondary reflections on the insides of the defects. Due to the secondary reflection these types of defects appear as a positive radius defect which then flips to a negative radius defect as illustrated earlier in [Figure 5.18](#). This is a key limitation of the current optical setup and processing pipeline as the 1D signal of these parts looks very similar to negative or positive radius defects due to the reflections. A solution could be to define heuristics for classifying such defects as they still appear in the reconstruction.

*RQ2: How can unsupervised learning methods be applied to segment reconstructed pipeline surfaces?*

1. *Which clustering algorithms provide the most interpretable and stable segmentation results?*

The second research question concerned the application of unsupervised clustering methods for segmenting 3D point clouds. By removing the dominant pipe wall through radial median filtering and residual analysis, the point cloud preprocessing stage effectively isolated defect related geometry and reduced clustering complexity. Among the evaluated methods, [DBSCAN](#) proved to be robust, fast, and scalable, particularly for elongated or continuous defects. Torque clustering offered greater flexibility and interpretability in some scenarios but was sensitive to feature scaling and exhibited unfavorable computational scaling for larger point clouds. The observed behavior confirms that density based methods are better suited for large scale inspection scenarios, while more complex hierarchical approaches require careful parameterization and further optimization to be practically applicable.

*RQ3: How can the quality of the segmentation and reconstruction be evaluated?*

1. *What metrics can be used to assess physical relevance?*
2. *How can segmented regions be visualized to support decision-making for integrity assessment?*

The third research question focused on reconstruction and segmentation quality evaluation and visualization. The use of quasi-synthetic reference point clouds enabled quantitative assessment through point-wise registration error and the [HD95](#). These metrics provided complementary insights, with point-wise registration error reflecting global geometric consistency and the [HD95](#) highlighting localized deviations caused by defects and outliers. Qualitative visualization in both Cartesian and polar domains further supported interpretation by clearly linking segmented regions to physical defect structures even finding accidentally introduced real defects. Together, these evaluation strategies demonstrated that the proposed pipeline produces physically meaningful segmentation for block like and positive radius defects, while also exposing weaknesses for complex or highly reflective geometries. Visualization was done using

radius (from the estimated center) estimation and cluster wise coloring.

In summary, this thesis demonstrates that **LPP** can support reliable 3D reconstruction and unsupervised segmentation for defect identification in drinking water pipelines under controlled conditions. The presented pipeline achieves millimeter scale accuracy, robust defect isolation, and efficient processing. At the same time, the results highlight important challenges related to material dependent reflectance, negative radius defect reconstruction, and the scalability of **TC**.

## 6.2. PRACTICAL AND SCIENTIFIC CONTRIBUTIONS

The main contribution of this research was that it used different techniques in **LPP** to go from image to a point cloud adjusted grid-based method, A\* for refining the laser profile and polar domain based processing and point cloud). Furthermore it compares the performance of **TC**, a merge graph pruning based approach, with **DBSCAN** on 3D point clouds resulting from **LPP**.

This research makes several practical and scientific contributions to the application of **LPP** for drinking water pipeline inspection. The primary contribution lies in the integration of multiple processing techniques to form a complete and coherent pipeline from raw image data to 3D point clouds. An adjusted grid-based circle center estimation method, polar domain processing, and A\* based laser line extraction were combined to achieve stable and accurate reconstructions under various imaging conditions. The explicit use of the polar domain simplified laser line extraction and subsequent geometric reasoning. In the case of concentric circles to use of n laser lines strengthened constraints and improved robustness during the grid-based center estimation.

In addition, this work demonstrates how **LPP** sourced point clouds can be prepared for unsupervised analysis by transforming dense pipe wall measurements into defect focused point clouds. The evaluation of **TC**, a merge graph pruning based clustering approach, on 3D point clouds derived from **LPP** represents a further scientific contribution. **TC** came out during this research which is why research on computational characteristics and usefulness in this specific application domain had not previously been explored. Together, these contributions show how established methods from computer vision, graph search, and unsupervised learning can be adapted and combined to address practical inspection problems in drinking water pipelines.

## 6.3. LIMITATIONS

Several limitations affect the scope and generalizability of the presented results. From an evaluation perspective, uncontrolled pitch, roll, and yaw and unknown speed during experimental data acquisition reduced the comparability between reconstructed point clouds and their quasi-synthetic references. While rotational corrections and frame wise longitudinal adjustments were made, variations in pitch and yaw introduced additional geometric deviations that increased the observed reconstruction error and limited the reliability of quantitative metrics. The 3D reconstructions themselves did not include any kinematic corrections.

The experimental validation was further constrained by the limited number of test scenarios. Only three experimental setups were evaluated quantitatively, and the range of materials was restricted to PVC pipes and a plastic barrel with a metal evaluation plate, which was only coated after testing so no comparisons were made there. As a result, the conclusions regarding robustness to material properties, surface reflectance, and environmental variation remain limited. In addition, only Euclidean distance based clustering algorithms were considered for segmentation. This restricts the exploration of alternative similarity measures or graph based representations that may better capture the underlying structure of defect geometry.

Finally, several implementation choices have influenced the performance of the overall data processing pipeline. In particular, image filtering and laser line extraction introduced a significant computational cost, which limits real time applicability in its current form. Furthermore the implementation of TC might have differed from the original as no source code is provided by the authors.

#### 6.4. FUTURE RESEARCH RECOMMENDATIONS

Future research can build on this work in multiple directions. First, performance can further be improved by using faster image filters and by increasing the robustness of circle center estimation (individual grids are not used in this work, only the row columns so a voting mechanism can be added), particularly in scenarios where laser lines are partially occluded by the robot itself. The sub method for finding peaks in a 1D signal from Subsection 4.4.2 can also be used instead of the one from Subsection 4.5.1 with some adjustments. Adaptive thresholds for pipe wall extraction may also improve defect isolation under varying conditions.

Furthermore the recorded images contain additional information beyond the laser lines. Laser diffusion provides sufficient illumination to reveal parts of the pipe interior, which could be exploited as a secondary data channel, further image preprocessing can enable this direction to be explored without requiring an additional input channel such as in previous research [17]. Combining laser based geometry with image based object detection or classification methods could support defect recognition, material identification, or contextual interpretation.

Point cloud representations could be further enhanced by incorporating reflection intensity, estimated material properties, or confidence measures derived from the image domain or other sources. The laser line extraction stage also offers opportunities for improvement. Instead of relying on explicit path finding, stricter graph construction rules, further sparsification or alternative line extraction algorithms could fully eliminate the need for a search while preserving robustness and achieving a one point wide profile.

Several geometric analyses remain unexplored. Ovality detection, for example, was not addressed, although the polar representation naturally lends itself to linear, sinusoidal, or more advanced fitting methods for detecting non circular cross sections. This can also be used for kinematics (pitch and yaw specifically) as those situations will result in the circle becoming an ellipse.

The sensing setup could be extended. This research works with a mono camera system, while multi sensor (n cameras, [IMU](#), [LiDAR](#) etc.) configurations could increase resolution and provide complementary information such as direct distance measurements, depth or motion estimates. Estimating kinematic parameters such as pitch and yaw from geometric assumptions or auxiliary sensors could improve frame alignment and evaluation reliability [\[21\]](#).

Finally on the segmentation side, only two distance based clustering algorithms were evaluated, while many other unsupervised and graph based methods remain available. A promising direction is to retain the point cloud as a graph structure and apply methods directly on it.



# REFERENCES

- [1] N. Wang, D. Ma, X. Du, B. Li, D. Di, G. Pang, Y. Duan. An automatic defect classification and segmentation method on three-dimensional point clouds for sewer pipes. *Tunnelling and Underground Space Technology* 143 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85174910800&doi=10.1016%2Fj.tust.2023.105480&partnerID=40&md5=aca0a93655813450b9bccf7743c7c9f1>. doi:10.1016/j.tust.2023.105480.
- [2] B. Kingdom, R. Liemberger, P. Marin, The Challenge of Reducing Non-Revenue Water in Developing Countries How the Private Sector Can Help: A Look at Performance-Based Service Contracting, World Bank, Washington, DC, 2006. doi:10.1596/17238.
- [3] Vewin, Drinking water factsheet, 2024. URL: <https://www.vewin.nl/wp-content/uploads/2024/09/Vewin-Drinking-Water-fact-Sheet.pdf>.
- [4] A. Oyama, H. Iida, Y. Ji, K. Umeda, Y. Mano, T. Yasui, T. Nakamura, volume 52, p. 87 – 90. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85077444292&doi=10.1016%2Fj.ifacol.2019.11.053&partnerID=40&md5=ecd2d30d1042d2bf53c7173fd539bb50>. doi:10.1016/j.ifacol.2019.11.053.
- [5] B. Rajani, Y. Kleiner. Non-destructive inspection techniques to determine structural distress indicators in water mains. *Evaluation and Control of Water Loss in Urban Networks* (2004).
- [6] R. Beuken, J. Eijkman, D. Savic, A. Hummelen, M. Blokker. Twenty years of asset management research for dutch drinking water utilities. *Water Supply* 20 (2020) 2941–2950. doi:10.2166/ws.2020.179.
- [7] J. v. Vossen, G. A. M. Mesman, T. P. H. van den Brand, J. Henzen, M. Nooijen, M. van de Wijst, H. Vogelaar, R. F. van Nieuwenhuijze, B. Jacobs, in: *Proceedings of the Pipeline Technology Conference 2017*, Pipeline Technology Conference, Estrel, Berlin, Germany. URL: [https://www.kwrwater.nl/wp-content/uploads/2016/05/Paper\\_Berlin\\_2017\\_8830\\_vossen\\_et\\_al.pdf](https://www.kwrwater.nl/wp-content/uploads/2016/05/Paper_Berlin_2017_8830_vossen_et_al.pdf).
- [8] K. van Laarhoven, J. van Steen, F. van der Hulst, H. Hernandez Delgadillo. Ct scans of asbestos cement pipes as a reference for condition assessment of water mains. *Water* 13 (2021) 2391. doi:10.3390/w13172391.
- [9] A. Khaled, R. El-Haibe, K. Grigoriadis, Y. Tang, M. Franchek, K. Yap, D. Bag. Multi-physics modeling of above-ground electromagnetic inspection on underground pipeline. *Journal of Nondestructive Evaluation* 44 (2025). doi:10.1007/s10921-025-01227-4.
- [10] S. Sampath, K. L. Chaurasiya, P. Aryan, B. Bhattacharya. An innovative approach towards defect detection and localization in gas pipelines using integrated in-line inspection methods. *Journal of Natural Gas Science and Engineering* 90 (2021) 103933. doi:10.1016/j.jngse.2021.103933.
- [11] C. H. Bahnsen, A. S. Johansen, M. P. Philipsen, J. W. Henriksen, K. Nasrollahi, T. B. Moeslund. 3d sensors for sewer inspection: A quantitative review and analysis. *Sensors* 21 (2021) 2553. doi:10.3390/s21072553.
- [12] M. Montoya, Y. Montelongo, N. Jiang, S. M. Morris, J. Parra-Michel. Free-form laser profilometry for pipeline inspection and 3d cylindrical reconstructions. *IEEE Sensors Journal* 22 (2022) 297 – 303. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85120580827&doi=10.1109/2fJSEN.2021.3130224&partnerID=40&md5=63617975b2e1a918d45daf3237b27cbf>. doi:10.1109/JSEN.2021.3130224.
- [13] M. Cao, X. Zhi, F. Ma, G. Luo, X. Chen, P. Ji, p. 247 – 252. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85191942012&doi=10.1109/2fIAEAC59436.2024.10503598&partnerID=40&md5=451d2e6c1bfbdb9fb72d1634b84508a0c>. doi:10.1109/IAEAC59436.2024.10503598.
- [14] H. Chen, G. Wen, X. He, S. Mei. A monocular structured light-based system for 3-d reconstruction and defect detection of municipal pipeline inner walls. *IEEE Sensors Journal* 25 (2025) 10309 – 10319. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105001063961&doi=10.1109/2fJSEN.2025.3532038&partnerID=40&md5=7534448c284f1a64db60c60bfae5cd0>. doi:10.1109/JSEN.2025.3532038.
- [15] X. Chen, F. Zhou, X. Chen, J. Yang. Mobile visual detecting system with a catadioptric vision sensor in pipeline. *Optik* 193 (2019). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85068028419&doi=10.1016%2Fj.ijleo.2019.05.060&partnerID=40&md5=ddde9d982a3f443caf16188595564802>. doi:10.1016/j.ijleo.2019.05.060.
- [16] Y. Liu, F. Zhou, Z. Guo, X. Li, X. Cheng, H. Tan. Pipeline inner surface 3d vision measuring system based on robot equipped with multi-directional structured-light sensor. *Measurement Science and Technology* 36 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105005492850&doi=10.1088%2F1361-6501%2Fadd610&partnerID=40&md5=4bf9b81ee9fbc7daadcfee01157d0166>. doi:10.1088/1361-6501/add610.
- [17] T. Tian, L. Wang, X. Yan, F. Ruan, G. J. Aadityaa, H. Choset, L. Li, p. 1525 – 1531. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85182526223&doi=10.1109/2fIROSS5552.2023.10341761&partnerID=40&md5=134578d59888a81019fa2bbc2d4f5807>. doi:10.1109/IROSS5552.2023.10341761.
- [18] A. Gunatilake, L. Piyaatilaka, A. Tran, V. K. Vishwanathan, K. Thiagarajan, S. Kodagoda. Stereo vision combined with laser profiling for mapping of pipeline internal defects. *IEEE Sensors Journal* 21 (2021) 11926–11934. doi:10.1109/jsen.2020.3040396.
- [19] S. Mukherjee, R. Zhang, M. Alzuheri, V. V. Rao, L. Udpa, Y. Deng. Inline pipeline inspection using hybrid deep learning aided endoscopic laser profiling. *Journal of Nondestructive Evaluation* 41 (2022). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85135407814&doi=10.1007%2fs10921-022-00890-1&partnerID=40&md5=2271497d8c572858668574ef136a8128>. doi:10.1007/s10921-022-00890-1.
- [20] Z. Wang, Z. Deng, P. Lei. Research on technology of pipeline detection robot based on spiral propulsion. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* 13016 LNAI (2021) 67 – 78. URL: [https://www.scopus.com/inward/record.uri?eid=2-s2.0-85118193415&doi=10.1007%2f978-3-030-89092-6\\_7&partnerID=40&md5=7d464365fa7cbed4cd2dbffdfc7c09](https://www.scopus.com/inward/record.uri?eid=2-s2.0-85118193415&doi=10.1007%2f978-3-030-89092-6_7&partnerID=40&md5=7d464365fa7cbed4cd2dbffdfc7c09). doi:10.1007/978-3-030-89092-6\_7.
- [21] M. Li, X. Feng, Q. Hu. 3d laser point cloud-based geometric digital twin for condition assessment of large diameter pipelines. *Tunnelling and Underground Space Technology* 142 (2023) 105430. doi:10.1016/j.tust.2023.105430.

- [22] Z. Yan, H. Zhao. Inner wall defect detection in oil and gas pipelines using point cloud data segmentation. *Automation in Construction* 173 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85219133626&doi=10.1016%2Fj.autcon.2025.106098&partnerID=40&md5=32a8a9eb56ab90fbde29d95ca3aad777>. doi:10.1016/j.autcon.2025.106098.
- [23] Y. Zhou, A. Ji, L. Zhang. Sewer defect detection from 3d point clouds using a transformer-based deep learning model. *Automation in Construction* 136 (2022) 104163. URL: <https://www.sciencedirect.com/science/article/pii/S092658052200036X>. doi:<https://doi.org/10.1016/j.autcon.2022.104163>.
- [24] Z. Zhang. A flexible new technique for camera calibration. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 22 (2000) 1330–1334. doi:10.1109/34.888718.
- [25] I. MathWorks, What is camera calibration?, website, 2025. URL: <https://nl.mathworks.com/help/vision/ug/camera-calibration.html>.
- [26] Q. Ma, W. Liang, P. Zhou. A review on pipeline in-line inspection technologies. *Sensors* 25 (2025) 4873. doi:10.3390/s25154873.
- [27] C. Du, K. Wang. Drainage pipeline defect detection system based on semantic segmentation. *Symmetry* 16 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85210418277&doi=10.3390%2Fsym16111477&partnerID=40&md5=053e977bf29534f6936627b10a1a3937>. doi:10.3390/sym16111477.
- [28] M. Alzuhiri, K. Farrag, E. Lever, Y. Deng. An electronically stabilized multi-color multi-ring structured light sensor for gas pipelines internal surface inspection. *IEEE Sensors Journal* 21 (2021) 19416–19426. doi:10.1109/jsen.2021.3086415.
- [29] H. Wang, C. Zhang, Y. Wang, P. Ni, Y. Wang. Segmentation of inner surface defects of stainless steel pipes based on semi-bilateral efficient self-attention network. *Journal of Nondestructive Evaluation* 44 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105001646465&doi=10.1007%2F10921-025-01176-y&partnerID=40&md5=8a209b1b5ba22385c25cd873067eb80b>. doi:10.1007/s10921-025-01176-y.
- [30] D. Sun, C. Yao, Y. Guo, C. Zhang, H. Ma, G. Pan. Pipeukan: Enhanced u-kan with edge attention for sewer pipe defect segmentation. *Communications in Computer and Information Science* 2575 CCIS (2025) 460 – 472. URL: [https://www.scopus.com/inward/record.uri?eid=2-s2.0-105013061095&doi=10.1007%2F978-981-95-0017-8\\_38&partnerID=40&md5=6b90573ee6fcd9296fef07784582ec81](https://www.scopus.com/inward/record.uri?eid=2-s2.0-105013061095&doi=10.1007%2F978-981-95-0017-8_38&partnerID=40&md5=6b90573ee6fcd9296fef07784582ec81). doi:10.1007/978-981-95-0017-8\_38.
- [31] M. Li, M. Li, Q. Ren, H. Li, L. Xiao, X. Fang. Pipetransunet: Cnn and transformer fusion network for semantic segmentation and severity quantification of multiple sewer pipe defects. *Applied Soft Computing* 159 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85192138110&doi=10.1016%2Fj.asoc.2024.111673&partnerID=40&md5=e0511611db1bf18c6c516651db180d>. doi:10.1016/j.asoc.2024.111673.
- [32] H. Feng, K. Song, W. Cui, Z. Zhou, Y. Yan. A suspected defect screening-guided lightweight network for few-shot aviation steel tube surface defect segmentation. *IEEE Sensors Journal* 24 (2024) 38113 – 38124. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85205827058&doi=10.1109%2FJSEN.2024.3449918&partnerID=40&md5=0f62f87cc0937d50d951451bd242bf17>. doi:10.1109/JSEN.2024.3449918.
- [33] N. Wang, J. Zhang, X. Song. A pipeline defect instance segmentation system based on sparseinst. *Sensors* 23 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85177799682&doi=10.3390%2Fs23229019&partnerID=40&md5=ed92a25bce35d87a200dbe32a59fddda>. doi:10.3390/s23229019.
- [34] D. Ma, H. Fang, N. Wang, H. Zheng, J. Dong, H. Hu. Automatic defogging, deblurring, and real-time segmentation system for sewer pipeline defects. *Automation in Construction* 144 (2022). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85138479784&doi=10.1016%2Fj.autcon.2022.104595&partnerID=40&md5=f17608c2ad12fefef9cf7418f049c37a>. doi:10.1016/j.autcon.2022.104595.
- [35] G. Pan, Y. Zheng, S. Guo, Y. Lv. Automatic sewer pipe defect semantic segmentation based on improved u-net. *Automation in Construction* 119 (2020). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85090247127&doi=10.1016%2Fj.autcon.2020.103383&partnerID=40&md5=a7555fbbd295cdf69ef553389aad4fa9>. doi:10.1016/j.autcon.2020.103383.
- [36] M. Wang, J. C. Cheng. A unified convolutional neural network integrated with conditional random field for pipe defect segmentation. *Computer-Aided Civil and Infrastructure Engineering* 35 (2020) 162 – 177. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85075283082&doi=10.1111%2Fmice.12481&partnerID=40&md5=9eedf27572b0d10221a023ae09ceb89d>. doi:10.1111/mice.12481.
- [37] W. Cao, Y. Zheng, J. Kang, X. Zhou, J. Zhang, in: *Proceedings of the 2025 5th International Conference on Robotics and Control Engineering, RobCE '25*, ACM, 2025, pp. 15–22. doi:10.1145/3733774.3735329.
- [38] H. Yang, L. Wang, Y. Pan, J. Chen. A teacher-student framework leveraging large vision model for data pre-annotation and yolo for tunnel lining multiple defects instance segmentation. *Journal of Industrial Information Integration* 44 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85217494840&doi=10.1016%2Fj.jii.2025.100790&partnerID=40&md5=0594bfa543d5bc822384a991d2150208>. doi:10.1016/j.jii.2025.100790.
- [39] L. Li, Y. Yang, M. Bian, Z. Li. Snakeconv and sfc boosting precise segmentation on the crack of tunnel lining surface: based on deeplabv3+ with improved swin transformer v2. *Measurement Science and Technology* 36 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85214655186&doi=10.1088%2F1361-6501%2Fada2b6&partnerID=40&md5=6230dec634bcab5b078c8d61118339e1>. doi:10.1088/1361-6501/ada2b6.
- [40] L. Feng, A. Yao, A. Huang. Tunnel crack segmentation algorithm based on feature enhancement. *IEEE Access* 13 (2025) 70650 – 70662. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105003699259&doi=10.1109%2FACCESS.2025.3562926&partnerID=40&md5=8b4f8ab61a7915bf40679af8c11ae3d0>. doi:10.1109/ACCESS.2025.3562926.
- [41] P. Wang, G. Shi. Image segmentation of tunnel water leakage defects in complex environments using an improved unet model. *Scientific Reports* 14 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85206560706&doi=10.1038%2Fs41598-024-75723-4&partnerID=40&md5=62935e2ab1f542675004dd57fd5746c5>. doi:10.1038/s41598-024-75723-4.
- [42] S. Qin, T. Qi, T. Deng, X. Huang. Image segmentation using vision transformer for tunnel defect assessment. *Computer-Aided Civil and Infrastructure Engineering* 39 (2024) 3243 – 3268. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85186460559&doi=10.1111%2Fmice.13181&partnerID=40&md5=0dd26760f44d6c4770081231eadde05e>. doi:10.1111/mice.13181.
- [43] L. Zhao, S. Hao, Z. Song. Context-aware semantic segmentation network for tunnel face feature identification. *Automation in Construction* 165 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85195806554&doi=10.1016%2Fj.autcon.2024.105560&partnerID=40&md5=27d3a786cdd14e8c8c8b74cf9ae9519ba>. doi:10.1016/j.autcon.2024.105560.

- [44] C. Zhang, X. Chen, P. Liu, B. He, W. Li, T. Song. Automated detection and segmentation of tunnel defects and objects using yolov8-cm. *Tunnelling and Underground Space Technology* 150 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85194459379&doi=10.1016%2Fj.tust.2024.105857&partnerID=40&md5=6c19280232bbe6462eafb7cc94999af4>. doi:10.1016/j.tust.2024.105857.
- [45] Y. Zhou, Z. Yang, X. Bai, C. Li, S. Wang, G. Peng, G. Li, Q. Wang, H. Chang. Semantic segmentation of surface cracks in urban comprehensive pipe galleries based on global attention. *Sensors* 24 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85184662656&doi=10.3390%2Fs24031005&partnerID=40&md5=4f9edaee8d0a944f79df209cbb2b8727>. doi:10.3390/s24031005.
- [46] D. Chen, Z. Zhu, J. Fu, J. He. Automatic road tunnel crack inspection based on crack area sensing and multiscale semantic segmentation. *Computers, Materials and Continua* 79 (2024) 1679 – 1703. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85191881489&doi=10.32604%2Fcmc.2024.049048&partnerID=40&md5=40b501f996470f2b319e8dd34bab17b6>. doi:10.32604/cmc.2024.049048.
- [47] Z. Zhou, L. Yan, J. Zhang, Y. Zheng, C. Gong, H. Yang, E. Deng. Automatic segmentation of tunnel lining defects based on multiscale attention and context information enhancement. *Construction and Building Materials* 387 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85158022404&doi=10.1016%2Fj.conbuildmat.2023.131621&partnerID=40&md5=893139a1ed5eff3ab154b305d359d3e4>. doi:10.1016/j.conbuildmat.2023.131621.
- [48] S. Feng, Y. Feng, X. Zhang, Y. Chen. Deep learning with visual explanations for leakage defect segmentation of metro shield tunnel. *Tunnelling and Underground Space Technology* 136 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85151272753&doi=10.1016%2Fj.tust.2023.105107&partnerID=40&md5=641085d22af02877713baacd036e2f9c>. doi:10.1016/j.tust.2023.105107.
- [49] Y. Xu, D. Li, Q. Xie, Q. Wu, J. Wang. Automatic defect detection and segmentation of tunnel surface using modified mask r-cnn. *Measurement: Journal of the International Measurement Confederation* 178 (2021). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85103974118&doi=10.1016%2Fj.measurement.2021.109316&partnerID=40&md5=93e4cc36b4c4f3dda09e38eae7903a70>. doi:10.1016/j.measurement.2021.109316.
- [50] X. Wan, X. Jiang, G. Luo, F. Sohel, J. Hwang. Flexicracknet: A flexible pipeline for enhanced crack segmentation with general features transferred from sam, 2025. doi:10.48550/ARXIV.2501.18855.
- [51] V. P. S. A. Chakraborty, A. K. Kar. How to undertake an impactful literature review: Understanding review approaches and guidelines for high-impact systematic literature reviews. *South Asian Journal of Business and Management Cases* 13 (2024) 18–35. URL: <https://doi.org/10.1177/22779779241227654>. doi:10.1177/22779779241227654.
- [52] C. Wohlin, in: *Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering, EASE '14, ACM, 2014*, pp. 1–10. doi:10.1145/2601248.2601268.
- [53] L. Colledge, R. Verlinde. *Scival metrics guidebook*. Netherlands: Elsevier 68 (2014).
- [54] M. Roznere, A. K. Pediredla, S. E. Lensgraf, Y. Girdhar, A. Q. Li, p. 6110 – 6117. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85202433417&doi=10.1109%2FICRA57147.2024.10611338&partnerID=40&md5=ec9a648367819d3ea64e17de5a4cc38b>. doi:10.1109/ICRA57147.2024.10611338.
- [55] Z. Wang, Z. Tang, J. Huang, J. Li. A real-time correction and stitching algorithm for underwater fisheye images. *Signal, Image and Video Processing* 16 (2022) 1783 – 1791. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85124967568&doi=10.1007%2Fs11760-022-02135-0&partnerID=40&md5=3e102ec2d8e6d98d403b87d5efd90840>. doi:10.1007/s11760-022-02135-0.
- [56] J. Kannala, S. Brandt. A generic camera model and calibration method for conventional, wide-angle, and fish-eye lenses. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 28 (2006) 1335–1340. doi:10.1109/TPAMI.2006.153.
- [57] X. Chen, Y. Zhang, X. Zhu, C. Liu, S. Wang, X. Deng. Multisensor fusion for 3-d reconstruction of urban pipeline interior using the enhanced r3live algorithm. *IEEE Sensors Journal* 25 (2025) 15830 – 15841. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-86000517589&doi=10.1109%2FJSEN.2025.3546981&partnerID=40&md5=6499ed313cc9cd77dc4af5b30de218fb>. doi:10.1109/JSEN.2025.3546981.
- [58] J. I. Fuentes-Guinez, G. Troni, H. Lobel. Splash-segformer pipeline: A transformer-based approach for high-resolution and low-cost laser scanner seafloor mapping. *IEEE Robotics and Automation Letters* (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105007555608&doi=10.1109%2FLRA.2025.3577520&partnerID=40&md5=9af18439658f34f48c5e7ccf8d34e79a>. doi:10.1109/LRA.2025.3577520.
- [59] Z. Zhang, A. Ji, L. Zhang, Y. Xu, Q. Zhou. Deep learning for large-scale point cloud segmentation in tunnels considering causal inference. *Automation in Construction* 152 (2023) 104915. URL: <https://www.sciencedirect.com/science/article/pii/S0926580523001759>. doi:https://doi.org/10.1016/j.autcon.2023.104915.
- [60] X. Zhang, X. Huang, K. Hong, Q. Li, R. Wang, B. Zhou. Tuc-net: A point cloud segmentation network based on neighborhood feature perception aggregation for tunnels under construction. *IEEE Transactions on Intelligent Transportation Systems* 26 (2025) 10048 – 10066. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85218792405&doi=10.1109%2FTITS.2025.3542500&partnerID=40&md5=8133023cf42174a2e04563c98650dd71>. doi:10.1109/TITS.2025.3542500.
- [61] Z. Li, N. Jiang, L. Tong. A few-shot learning-based point cloud semantic segmentation network for tunnel lining inspection. *IET Signal Processing* 2025 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105005163718&doi=10.1049%2Fsi12%2F6624103&partnerID=40&md5=35a1c584e15d91f57cfe132653cb173d>. doi:10.1049/si12/6624103.
- [62] J. Li, Z. Zhang, H. Sun, S. Xie, J. Zou, C. Ji, Y. Lu, X. Ren, L. Wang. Gl-net: Semantic segmentation for point clouds of shield tunnel via global feature learning and local feature discriminative aggregation. *ISPRS Journal of Photogrammetry and Remote Sensing* 199 (2023) 335 – 349. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85153676380&doi=10.1016%2Fj.isprsjprs.2023.04.011&partnerID=40&md5=f2dc11c97f5748be4430ae67f65c62d4>. doi:10.1016/j.isprsjprs.2023.04.011.
- [63] S. Liu, H. Sun, Z. Zhang, Y. Li, R. Zhong, J. Li, S. Chen. A multiscale deep feature for the instance segmentation of water leakages in tunnel using mls point cloud intensity images. *IEEE Transactions on Geoscience and Remote Sensing* 60 (2022). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85126331096&doi=10.1109%2FTGRS.2022.3158660&partnerID=40&md5=1c16c33cad8cbb868b64f077f0dc2496>. doi:10.1109/TGRS.2022.3158660.
- [64] T. Zhang, L. Cui, L. Zhou, J. Liu, L. Kou, Q. Xie. A roughness, feature-based algorithm of point cloud segmentation of the secondary lining in natm tunnel. *Acta Polytechnica Hungarica* 22 (2025) 193 – 212. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85215098502&doi=10.12700%2FAPH.22.4.2025.4.12&partnerID=40&md5=f86a78d59f8c45d858ccca1a9b1c6c29>. doi:10.12700/APH.22.4.2025.4.12.

- [65] P. Alcantarilla, J. Nuevo, A. Bartoli, in: Proceedings of the British Machine Vision Conference 2013, BMVC 2013, British Machine Vision Association, 2013, pp. 13.1–13.11. doi:[10.5244/c.27.13](https://doi.org/10.5244/c.27.13).
- [66] J. Shi, Tomasi, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition CVPR-94, IEEE Comput. Soc. Press, 1994, pp. 593–600. doi:[10.1109/cvpr.1994.323794](https://doi.org/10.1109/cvpr.1994.323794).
- [67] B. D. Lucas, T. Kanade, in: Proceedings of the 7th International Joint Conference on Artificial Intelligence - Volume 2, IJCAI'81, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1981, p. 674–679.
- [68] Y. Dong, C. Fang, L. Zhu, N. Yan, X. Zhang. The calibration method of the circle-structured light measurement system for inner surfaces considering systematic errors. Measurement Science and Technology 32 (2021) 075012. doi:[10.1088/1361-6501/abe288](https://doi.org/10.1088/1361-6501/abe288).
- [69] H. Yin, Y. Gong, G. Qiu, Side window filtering, 2019. doi:[10.48550/ARXIV.1905.07177](https://doi.org/10.48550/ARXIV.1905.07177).
- [70] C. Steger. An unbiased detector of curvilinear structures. IEEE Transactions on Pattern Analysis and Machine Intelligence 20 (1998) 113–125. doi:[10.1109/34.659930](https://doi.org/10.1109/34.659930).
- [71] D. Cheng, H. Shi, M. Schwerin, M. Crivella, L. Li, H. Choset, in: 2020 IEEE SENSORS, IEEE, 2020, pp. 1–4. doi:[10.1109/sensors47125.2020.9278586](https://doi.org/10.1109/sensors47125.2020.9278586).
- [72] D. Scaramuzza, A. Martinelli, R. Siegwart. doi:[10.1109/IR0S.2006.282372](https://doi.org/10.1109/IR0S.2006.282372).
- [73] F. Zhou, X. Chen, H. Tan, X. Chai. Calibrating non-central catadioptric vision system using local target reconstruction. Measurement Science and Technology 28 (2017) 065009. doi:[10.1088/1361-6501/aa6784](https://doi.org/10.1088/1361-6501/aa6784).
- [74] F. Zhou, G. Zhang. Complete calibration of a structured light stripe vision sensor through planar target of unknown orientations. Image and Vision Computing 23 (2005) 59–67. doi:[10.1016/j.imavis.2004.07.006](https://doi.org/10.1016/j.imavis.2004.07.006).
- [75] L. Heng, B. Li, M. Pollefeys, in: 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, 2013. doi:[10.1109/iros.2013.6696592](https://doi.org/10.1109/iros.2013.6696592).
- [76] S. Huber, H. Wiemer, D. Schneider, S. Ihlenfeldt. Dmme: Data mining methodology for engineering applications – a holistic extension to the crisp-dm model. Procedia CIRP 79 (2019) 403–408. doi:[10.1016/j.procir.2019.02.106](https://doi.org/10.1016/j.procir.2019.02.106).
- [77] R. Wirth, J. Hipp, in: Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining, pp. 29–39. URL: <https://cs.unibo.it/~daniilo.montesi/CBD/Beatriz/10.1.1.198.5133.pdf>.
- [78] E. S. L. Gastal, M. M. Oliveira, in: ACM SIGGRAPH 2011 papers, volume 30 of SIGGRAPH '11, ACM, 2011, pp. 69:1–69:12. doi:[10.1145/1964921.1964964](https://doi.org/10.1145/1964921.1964964).
- [79] G. Jiang, L. Quan, volume I, p. 333 – 340. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-33745963057&partnerID=40&md5=69b74b6541254d0b6fb076249e415725>.
- [80] A. A. Hagberg, D. A. Schult, P. J. Swart, in: G. Varoquaux, T. Vaught, J. Millman (Eds.), Proceedings of the 7th Python in Science Conference, Pasadena, CA USA, pp. 11 – 15.
- [81] M. Ester, H.-P. Kriegel, J. Sander, X. Xu, p. 226 – 231. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85170282443&partnerID=40&md5=bbefa1633035b0779ae320a55ac5323a>.
- [82] J. Yang, C.-T. Lin. Autonomous clustering by fast find of mass and distance peaks. IEEE Transactions on Pattern Analysis and Machine Intelligence 47 (2025) 5336–5349. doi:[10.1109/tpami.2025.3535743](https://doi.org/10.1109/tpami.2025.3535743).
- [83] T. Y. Zhang, C. Y. Suen. A fast parallel algorithm for thinning digital patterns. Communications of the ACM 27 (1984) 236–239. doi:[10.1145/357994.358023](https://doi.org/10.1145/357994.358023).
- [84] P. Besl, N. D. McKay. A method for registration of 3-d shapes. IEEE Transactions on Pattern Analysis and Machine Intelligence 14 (1992) 239–256. doi:[10.1109/34.121791](https://doi.org/10.1109/34.121791).
- [85] S. Long, T. Yang, Y. Qian, Y. Wu, F. Xu, Q. Tang, F. Guo. Gpr imagery-based internal defect evaluation system for railroad tunnel lining using real-time instance segmentation. IEEE Sensors Journal 24 (2024) 35997 – 36010. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85204342636&doi=10.1109/2FJSEN.2024.3456093&partnerID=40&md5=d74cadbf2e0b657f66b969d6d6effb30>. doi:[10.1109/JSEN.2024.3456093](https://doi.org/10.1109/JSEN.2024.3456093).
- [86] S. Zbirovský, V. Nežerka. Open-source automatic pipeline for efficient conversion of large-scale point clouds to ifc format. Automation in Construction 177 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105007477309&doi=10.1016/2Fj.autcon.2025.106303&partnerID=40&md5=7cc7db52e2efd5b30354d67c46da893e>. doi:[10.1016/j.autcon.2025.106303](https://doi.org/10.1016/j.autcon.2025.106303).
- [87] R. Castro Aguiar, E. J. Sam Jeeva Raj, S. Chakrabarty. Simplified markerless stride detection pipeline (smasdp) for surface emg segmentation. Sensors 23 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85159287342&doi=10.3390/2Fs23094340&partnerID=40&md5=902df604b8896e961fac984ac2b1fd65>. doi:[10.3390/s23094340](https://doi.org/10.3390/s23094340).
- [88] L. Xie, X. Zhang, D. Tu, C. Li, G. Xiao, C. Zhang, S. Zhuang. Calibration of underwater fisheye camera with multi-frequency heterodyne technique based on light field. Measurement Science and Technology 31 (2020). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85092645870&doi=10.1088/2f1361-6501/2faba232&partnerID=40&md5=189dfaa84bc23f9e6d5e0c92800bbb2>. doi:[10.1088/1361-6501/aba232](https://doi.org/10.1088/1361-6501/aba232).
- [89] R. Tenscher-Philipp, T. Schanz, F. Harlacher, B. Fautz, M. Simon. Ai-driven synthetization pipeline of realistic 3d-ct data for industrial defect segmentation. Journal of Nondestructive Evaluation 43 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85193583591&doi=10.1007/2Fs10921-024-01080-x&partnerID=40&md5=7afe14466d1132df234424ba49784119>. doi:[10.1007/s10921-024-01080-x](https://doi.org/10.1007/s10921-024-01080-x).
- [90] J. Luo, C. You, B. Zheng. Adversarial dual-distortion image rectification: Integrating multi-scale discriminators and central self-attention modules. IEEE Access 13 (2025) 109172–109184. doi:[10.1109/access.2025.3582046](https://doi.org/10.1109/access.2025.3582046).
- [91] Y. Huang, X. Shengwang, X. Xing, H. Qiu. Litepipenet: Research on a lightweight and efficient segmentation model for uav pipeline inspection in mining areas. IEEE Access 13 (2025) 126886 – 126900. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105010306374&doi=10.1109/2FACCESS.2025.3587196&partnerID=40&md5=fadd36b23c4fb74fdc14fe6579142cf9>. doi:[10.1109/ACCESS.2025.3587196](https://doi.org/10.1109/ACCESS.2025.3587196).

- [92] L. Falqueto, D. Butkus, J. De Mello, A. Bozzi, C. Scandian. Sliding wear of cobalt-based alloys used in rolling seamless tubes. *Wear* 376-377 (2017) 1739 – 1746. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85020829721&doi=10.1016%2fj.wear.2017.01.009&partnerID=40&md5=b8b0077314f4a6bc5434d5ed0c21a7f5>. doi:10.1016/j.wear.2017.01.009.
- [93] S. Soria, A. Tolley, A. Yawny. Characterization of damage and tribo-particles resulting from fretting of incoloy 800 steam generator tubes against different materials. *Wear* 390-391 (2017) 198 – 208. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85026922401&doi=10.1016%2fj.wear.2017.07.022&partnerID=40&md5=e746ee338693d8b1d874dfcebd2c5809>. doi:10.1016/j.wear.2017.07.022.
- [94] Z. Xiao, X. Zhang, Y. Liu, L. Geng, J. Wu, W. Wang, F. Zhang. Rnn-combined graph convolutional network with multi-feature fusion for tuberculosis cavity segmentation. *Signal, Image and Video Processing* 17 (2023) 2297 – 2303. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85145708890&doi=10.1007%2f511760-022-02446-2&partnerID=40&md5=46a10595c95bd9788f9f64c33fb82d83>. doi:10.1007/s11760-022-02446-2.
- [95] E. Gamsjäger, M. Lin, W. A. Tichauer, M. Militzer. In-situ austenite grain growth measurements in an x80 line pipe steel. *Materials Characterization* 224 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105001869187&doi=10.1016%2fj.matchar.2025.114998&partnerID=40&md5=697aaa264631ef2a8e565f9f867d82a1>. doi:10.1016/j.matchar.2025.114998.
- [96] T. A. Jack, J. Szpunar. Direct observation of the influence of grain orientation on the corrosion of pipeline steels. *Materials Characterization* 222 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85217960757&doi=10.1016%2fj.matchar.2025.114836&partnerID=40&md5=c9b1b6490f77c1d22b0e663487856190>. doi:10.1016/j.matchar.2025.114836.
- [97] H. Wang, Q. Wang, W. Zhang, J. Zhai, D. Yuan, J. Tong, X. Xie, B. Zhou, H. Tian. A deep learning-based watershed feature fusion approach for tunnel crack segmentation in complex backgrounds. *Materials* 18 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85214448374&doi=10.3390%2fma18010142&partnerID=40&md5=54864c6c49bc11e630d4ecfeecbadf>. doi:10.3390/ma18010142.
- [98] G. Zaburda, A. Onnala, K. Cichy, J. Daguin, A. J. G. Lunt. Mechanical and microstructural characterisation of cooling pipes for the compact muon solenoid experiment at cern. *Materials* 14 (2021). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85108321638&doi=10.3390%2fma14123190&partnerID=40&md5=37b0c48c50f5e33994b4e0bdb5cef2e2>. doi:10.3390/ma14123190.
- [99] J. Daniel, A. Abudhahir, J. J. Paulin. Tsallis entropy segmentation and shape feature-based classification of defects in the simulated magnetic flux leakage images of steam generator tubes. *International Journal of Pattern Recognition and Artificial Intelligence* 34 (2020). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85066886999&doi=10.1142%2fS0218001420540026&partnerID=40&md5=a30dfb5e6faf427cf7cfe8752450b8bf>. doi:10.1142/S0218001420540026.
- [100] Z. Chao, F. Wang, C. Zhang, H. Li, F. Wang. Research on the algorithm of measurement path planning for inner wall of air-intake pipe based on spraying robot system. *International Journal of Pattern Recognition and Artificial Intelligence* 31 (2017). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85016494475&doi=10.1142%2fS0218001417590182&partnerID=40&md5=0ecc23ba7da6406db146b024edbabde>. doi:10.1142/S0218001417590182.
- [101] L. Xingfeng, Z. Ying, C. Yongxin, C. Jian, C. Yuguang. Study on the fractal-stress state correlation of pipeline steel fracture surfaces based on three-dimensional reconstruction. *Engineering Failure Analysis* 175 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105001843170&doi=10.1016%2fj.engfailanal.2025.109570&partnerID=40&md5=031726cc09f72aa7fab98034fad1fac7>. doi:10.1016/j.engfailanal.2025.109570.
- [102] H. Pourmohammad, A. Bahrami, A. Eslami, M. Taghipour. Failure investigation on a radiant tube in an ethylene cracking unit. *Engineering Failure Analysis* 104 (2019) 216 – 226. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85066869776&doi=10.1016%2fj.engfailanal.2019.05.042&partnerID=40&md5=75c3ed0bb64067e7e0da6f0c328f2d19>. doi:10.1016/j.engfailanal.2019.05.042.
- [103] S. Yang, Z. Wang, J. Wang, A. G. Cohn, J. Zhang, P. Jiang, L. Nie, Q. Sui. Defect segmentation: Mapping tunnel lining internal defects with ground penetrating radar data using a convolutional neural network. *Construction and Building Materials* 319 (2022). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85121527332&doi=10.1016%2fj.conbuildmat.2021.125658&partnerID=40&md5=1e07a84a691581b7b64c734c4e7c500a>. doi:10.1016/j.conbuildmat.2021.125658.
- [104] OpenCV, Camera calibration and 3d reconstruction, 2025. URL: [https://docs.opencv.org/4.x/d9/d0c/group\\_\\_calib3d.html](https://docs.opencv.org/4.x/d9/d0c/group__calib3d.html).
- [105] T. Wu, S. Lu, Y. Tang, in: 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), IEEE, 2015, pp. 2637–2641. doi:10.1109/fskd.2015.7382373.
- [106] C. Sepulveda-Valdez, O. Sergiyenko, R. Alaniz-Plata, J. A. Núñez-López, V. Tyras, W. Flores-Fuentes, J. C. Rodríguez-Quinones, P. Mercorelli, M. Kolendovska, V. Kartashov, J. E. Miranda-Vega, F. N. Murrieta-Rico, in: IECON 2023- 49th Annual Conference of the IEEE Industrial Electronics Society, IEEE, 2023, pp. 1–6. doi:10.1109/iecon51785.2023.10312684.
- [107] J. Xiang, Y. Li, J. Li, W. Zheng, Q. Fu. Self-calibrating fisheye lens aberrations for novel view synthesis. *Computer Graphics Forum* (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105002250979&doi=10.1111%2fcgf.70148&partnerID=40&md5=0c71eabe4de9fad3e8abd6e5bc56c4b8>. doi:10.1111/cgf.70148.
- [108] L.-W. Hung, J. White, D. Joyce, S. J. Anderson, B. Banet. Fisheye night sky imager: A calibrated tool to measure night sky brightness. *Publications of the Astronomical Society of the Pacific* 136 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85202830390&doi=10.1088%2f1538-3873%2fad6bc1&partnerID=40&md5=04f33eb047b645b1a49da700471c7a18>. doi:10.1088/1538-3873/ad6bc1.
- [109] J. Hu, Z. Ning, H. Jie, L. Liu, H. Yu, J. Lv. Automatic calibration method for high resolution lidar and fisheye camera. *Smart Innovation, Systems and Technologies* 374 (2024) 353 – 362. URL: [https://www.scopus.com/inward/record.uri?eid=2-s2.0-85181984362&doi=10.1007%2f978-981-99-70111-7\\_29&partnerID=40&md5=6123b394504e99e48c085a85e699e368](https://www.scopus.com/inward/record.uri?eid=2-s2.0-85181984362&doi=10.1007%2f978-981-99-70111-7_29&partnerID=40&md5=6123b394504e99e48c085a85e699e368). doi:10.1007/978-981-99-70111-7\_29.
- [110] M. Syafiq, I.-Y. Rau, J.-P. Jhan, volume 48, p. 237 – 242. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85144313094&doi=10.5194%2fisprs-archives-XLVIII-2-W1-2022-237-2022&partnerID=40&md5=a0961752b3ee843a7800b8205b7624fa>. doi:10.5194/isprs-archives-XLVIII-2-W1-2022-237-2022.
- [111] V. R. Kumar, S. Yogamani, M. Bach, C. Witt, S. Milz, P. Mader, p. 8177 – 8183. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85099656455&doi=10.1109%2fIRO545743.2020.9340732&partnerID=40&md5=c38b25a0126e7dad3ea271bf1bdeee87>. doi:10.1109/IRO545743.2020.9340732.
- [112] X. Liu, R. Ji, H. Wang, M. Fu, B. Zheng, M. Sun, J. Qin, C. Zhen. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85104595917&doi=10.1109%2fIEEECONF38699.2020.9389352&partnerID=40&md5=558d4284aeb9b5bde75eb1e76598467f>. doi:10.1109/IEEECONF38699.2020.9389352.



- [113] Y. Liu, B. Zhang, N. Liu, H. Li, J. Zhu, p. 1066 – 1070. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85096524403&doi=10.1109/2fICMA49215.2020.9233684&partnerID=40&md5=d2b374fc1c313b5b9cd2451a8ac89798>. doi:10.1109/ICMA49215.2020.9233684.
- [114] M. Zeng, S. Wu, F. Li, G. Hu, p. 119 – 124. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85116628305&doi=10.1109/2fICDSBA51020.2020.00038&partnerID=40&md5=e3aef64ef8e924f7b1db99e2ecb3a000>. doi:10.1109/ICDSBA51020.2020.00038.
- [115] M. Xu, volume 300. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85071490680&doi=10.1088/2f1755-1315/2f300/2f2/2f022075&partnerID=40&md5=01c0d49045d3a585515969d4bb084a98>. doi:10.1088/1755-1315/300/2/022075.
- [116] C. Häne, L. Heng, G. H. Lee, F. Fraundorfer, P. Furgale, T. Sattler, M. Pollefeys. 3d visual perception for self-driving cars using a multi-camera system: Calibration, mapping, localization, and obstacle detection. *Image and Vision Computing* 68 (2017) 14 – 27. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85028449152&doi=10.1016/2fj.imavis.2017.07.003&partnerID=40&md5=ef7459a8308ae65b34da42d2a4f12028>. doi:10.1016/j.imavis.2017.07.003.
- [117] F. Jesus Martinez Martinez, L. Blum, S. Rider, A. Cárdenas, D. Piovesan, volume 3. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85041000744&doi=10.1115/2fIMECE2017-71795&partnerID=40&md5=100836bfaf87d4301f10a61e0c564d25>. doi:10.1115/IMECE2017-71795.
- [118] L. Qin, C. Lin, S. Huang, S. Yang, Y. Zhao, Camera calibration for the surround-view system: a benchmark and dataset, 2023. URL: <https://arxiv.org/abs/2312.16499>. arXiv:2312.16499.
- [119] F. Huo, W. Wu, H. Dong, W. Ren, K. Liu. A novel stereoscopic calibration apparatus and method based on a large wide- angle fisheye lens (2025). doi:10.2139/ssrn.5093178.
- [120] G. Wu, H. Zhang, Z. Yan, H. Wang, Z. Zhong, Z. Yin, volume 12969. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85182995003&doi=10.1117/2f12.3014403&partnerID=40&md5=209974815f74cc254af975a01e3d78f9>. doi:10.1117/12.3014403.
- [121] L. Stausberg, B. Jost, L. Klingbeil, H. Kuhlmann. A 3d surface reconstruction pipeline for plant phenotyping. *Remote Sensing* 16 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85213286245&doi=10.3390/2frs16244720&partnerID=40&md5=026b720c322236981bd ec0d69a35a746>. doi:10.3390/rs16244720.
- [122] C. Aprameya, S. Joladarashi, M. Ramesh. Investigation of high-temperature wear behaviour of mo-alloyed ss316 laser claddings deposited by lded for heat exchanger tubes. *Next Materials* 9 (2025) 101051. doi:10.1016/j.nxmte.2025.101051.
- [123] S. Karam, M. Peter, S. Hosseinyalamdary, G. Vosselman, volume 4, p. 85 – 92. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85056349880&doi=10.5194/2fispr-annals-IV-1-85-2018&partnerID=40&md5=15cff112a15a09c322ac8ba5dc8948a3>. doi:10.5194/ispr-annals-IV-1-85-2018.
- [124] J. Lin, W. Zhou, X. Cui, H. Hong. Application of wavelet transforms to the simulation of corrosion fields on buried pipelines. *Computers and Structures* 276 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85144336748&doi=10.1016/2fj.compstruc.2022.106957&partnerID=40&md5=fa16183255970ac61820d3829546c554>. doi:10.1016/j.compstruc.2022.106957.
- [125] J. Hall, M. Daniszewski, S. Cheung, K. Shobhana, H. Kumar, H. H. Liang, H. Beetham, E. Cho, C. Abbott, A. W. Hewitt, K. J. Simpson, R. H. Guymer, D. Paull, A. Pébay, G. E. Lidgerwood. A semi-automated pipeline for quantifying drusen-like deposits in human induced pluripotent stem cell-derived retinal pigment epithelium cells. *SLAS Technology* 29 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85195708631&doi=10.1016/2fj.slact.2023.08.006&partnerID=40&md5=71fb2929097e44cc5a8a8970a87ea0e5>. doi:10.1016/j.slact.2023.08.006.
- [126] L. Hart, S. Knoblach, M. Möser. Automated pipeline reconstruction using deep learning & instance segmentation. *ISPRS Open Journal of Photogrammetry and Remote Sensing* 9 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85182612175&doi=10.1016/2fj.ophoto.2023.100043&partnerID=40&md5=49eec5712b82292236cb8e98ca36e03f>. doi:10.1016/j.ophoto.2023.100043.
- [127] S. Siviu, M. Ioan, B. Marius, S. Cornel, volume 9258. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84924259037&doi=10.1117/2f12.2070423&partnerID=40&md5=dd5a76e83a1535b4a5c60721a1d4db93>. doi:10.1117/12.2070423.
- [128] C. Madsen, Y. Dogan, J. Lin. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85102574344&partnerID=40&md5=a94ee8474d19e37b38d806e35aee5737>.
- [129] R. M. Rodrigues, D. A. Thadathil, G. Shanker, U. Sirimahachai, A. Varghese, G. Hegde. Co-electrodeposited pi-mno2-rgo as an efficient electrode for the selective oxidation of piperonyl alcohol. *Journal of the Electrochemical Society* 170 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85149510102&doi=10.1149/2f1945-7111/2facbdc2&partnerID=40&md5=caa2605f3f5295a70baa64c8ecc25e3a>. doi:10.1149/1945-7111/acbdc2.
- [130] R. Forte, F. Berrilli, D. Calchetti, D. Del Moro, B. Fleck, C. Giebink, W. Giebink, L. Giovannelli, S. M. Jefferies, A. Knox, M. Magri, N. Murphy, G. Nitta, M. Oliviero, E. Pietropaolo, W. Rodgers, S. Scardigli, G. Viavattene. Data reduction pipeline for mof-based synoptic telescopes. *Journal of Space Weather and Space Climate* 10 (2020). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85096479319&doi=10.1051/2fswsc/2f2020065&partnerID=40&md5=b957dd574e88cf9b7856ef2c48cf8df7>. doi:10.1051/swsc/2020065.
- [131] J. Lin, W. Zhou. Discrete wavelet analysis of external corrosion clusters on pipelines for burst capacity prediction. *International Journal of Pressure Vessels and Piping* 206 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85174828754&doi=10.1016/2fj.ijpvp.2023.105075&partnerID=40&md5=18541b7ba2f41688c3369058ce197b3c>. doi:10.1016/j.ijpvp.2023.105075.
- [132] N. Sarhangnejad, N. Katic, Z. Xia, M. Wei, N. Gusev, G. Dutta, R. Gulve, P. Z. X. Li, H. F. Ke, H. Haim, M. Moreno-Garcia, D. Stoppa, K. N. Kutulakos, R. Genov. Dual-tap computational photography image sensor with per-pixel pipelined digital memory for intra-frame coded multi-exposure. *IEEE Journal of Solid-State Circuits* 54 (2019) 3191 – 3202. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85074402143&doi=10.1109/2fJSSC.2019.2932623&partnerID=40&md5=75e362aa24fd011682910ea11e653a1d>. doi:10.1109/JSSC.2019.2932623.
- [133] Z. Tian, B. Liang, H. Fang, D. Weng. Dynamic 4d facial capture pipeline with appearance driven progressive retopology based on optical flow. *Optics Express* 32 (2024) 31830 – 31848. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85202660293&doi=10.1364/2fOE.529846&partnerID=40&md5=010e333198bdd77cd089f1881625b5ed>. doi:10.1364/OE.529846.
- [134] I. Mihai, S. Sprinceana, volume 10010. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85010868373&doi=10.1117/2f12.2242992&partnerID=40&md5=18902a1684c0cb91d7936733d371d367>. doi:10.1117/12.2242992.

- [135] L. Ebert, P. Flach, W. Schweitzer, A. Leipner, S. Kottner, D. Gascho, M. Thali, R. Breitbeck. Forensic 3d surface documentation at the institute of forensic medicine in zurich - workflow and communication pipeline. *Journal of Forensic Radiology and Imaging* 5 (2016) 1 – 7. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84958976288&doi=10.1016%2fj.jofri.2015.11.007&partnerID=40&md5=c6e104722b720cfc8acc3fc90f3ef7c4>. doi:10.1016/j.jofri.2015.11.007.
- [136] J. Nieto-Fuentes, J. Espinoza, F. Sket, J. Rodríguez-Martínez. High-velocity impact fragmentation of additively-manufactured metallic tubes. *Journal of the Mechanics and Physics of Solids* 174 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85149185526&doi=10.1016%2fj.jmps.2023.105248&partnerID=40&md5=9a5bf24fd29f013da6b216366bc2a533>. doi:10.1016/j.jmps.2023.105248.
- [137] R. A. Bickham. Influence of flow and impurities on carbon steel pipelines. *Materials Performance* 60 (2021) 16 – 19. URL: [https://www.scopus.com/inward/record.uri?eid=2-s2.0-105001256733&doi=10.5006%2fmp2021\\_60\\_8-16&partnerID=40&md5=6b2f58def2861ac874ec741857c21d74](https://www.scopus.com/inward/record.uri?eid=2-s2.0-105001256733&doi=10.5006%2fmp2021_60_8-16&partnerID=40&md5=6b2f58def2861ac874ec741857c21d74). doi:10.5006/mp2021\_60\_8-16.
- [138] G. Mettivier, F. Di Franco, A. Sarno, R. Castriconi, F. Di Lillo, K. Bliznakova, P. Russo. In-line phase contrast mammography, phase contrast digital breast tomosynthesis, and phase contrast breast computed tomography with a dedicated ct scanner and a microfocus x-ray tube: Experimental phantom study. *IEEE Transactions on Radiation and Plasma Medical Sciences* 5 (2021) 793 – 806. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-5112733947&doi=10.1109%2fTRPMS.2020.3003380&partnerID=40&md5=13c022629e647b3fc4ba793ba6716d9d>. doi:10.1109/TRPMS.2020.3003380.
- [139] C.-M. Kuo, T.-H. Lin, C.-Y. Chen, volume 2, p. 868 – 871. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85056178012&partnerID=40&md5=05ce84067ff05fa820cf6b998815239c>.
- [140] V. Savin, L. Savina, K. Lebedeva, A. Osadchy, A. Lykoshva, A. Martyushev, V. Gerilovich, I. Zhuravlev, volume 2486. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85143054149&doi=10.1063%2f5.0107358&partnerID=40&md5=7ab3eb39842ceb7dbce99f57fbdcc5cc6>. doi:10.1063/5.0107358.
- [141] C. Hagemann, M. C. Bailey, E. Carraro, K. S. Stankevich, V. M. Lionello, N. Khokhar, P. Suklai, C. Moreno-Gonzalez, K. O'Toole, G. Konstantinou, C. L. Dix, S. Joshi, E. Giagnorio, M. S. Bergholt, C. D. Spicer, A. Imbert, F. S. Tedesco, A. Serio. Low-cost, versatile, and highly reproducible microfabrication pipeline to generate 3d-printed customised cell culture devices with complex designs. *PLoS Biology* 22 (2024). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85187732853&doi=10.1371%2fjournal.pbio.3002503&partnerID=40&md5=143dae3a1180645f22c617c2e498062>. doi:10.1371/journal.pbio.3002503.
- [142] S. d. F. M. Mariano, M. Ueda, R. M. Oliveira, E. J. d. D. M. Pillaca, N. M. d. Santos. Magnetic-field enhanced plasma immersion ion implantation and deposition (pii&d) of diamond-like carbon films inside tubes. *Surface and Coatings Technology* 312 (2017) 47 – 54. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84994895277&doi=10.1016%2fj.surfcoat.2016.08.077&partnerID=40&md5=817893e34ff61b993a3c6741cb65b2df>. doi:10.1016/j.surfcoat.2016.08.077.
- [143] D. Hermawanto, K. Ishikawa, K. Yatabe, Y. Oikawa. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85059364950&partnerID=40&md5=fe5cf9bab5e0ab67b6aaeb7cdb8dadfb>.
- [144] K. Kurita, M. Nakagawa. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85127457068&partnerID=40&md5=8bc1c1e5fe5bc891264df6c2ffa1c07b>.
- [145] E. Conti, S. Dattilo, A. Scamporrino, G. Costa, F. Samperi. Novel amino acid assembly in the silk tubes of arid-adapted segestriid spiders. *Journal of Chemical Ecology* 46 (2020) 48 – 62. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85076315745&doi=10.1007%2fs10886-019-01127-8&partnerID=40&md5=0a94bee8e145e22ffbc10485fe6efa81>. doi:10.1007/s10886-019-01127-8.
- [146] G. A. Idrobo-Pizo, J. M. S. Motta, D. L. Borges. Novel invariant feature descriptor and a pipeline for range image registration in robotic welding applications. *IET Image Processing* 13 (2019) 964 – 974. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85065253799&doi=10.1049%2fiet-ipr.2018.6105&partnerID=40&md5=5c1aae53c52193b1cb958d0b74f7b76e>. doi:10.1049/iet-ipr.2018.6105.
- [147] I. Mihai, S. Sprinceana, C. Suciu, volume 10977. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85061161875&doi=10.1117%2f12.2323405&partnerID=40&md5=032072edf99a2c8dc030e433622cedf2>. doi:10.1117/12.2323405.
- [148] I. Bartoň, V. Matějček, J. Mrázek, O. Podrazký, volume 9450. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84923052564&doi=10.1117%2f12.2070253&partnerID=40&md5=04ee843d2e6301ec2182f691a8b232f8>. doi:10.1117/12.2070253.
- [149] Z. Li, R. Zhu, Y. Gao, C. H. Chim, H. Liao. Recrystallization of holocene calcareous root tubes in the tengger desert, northwest china and its effects on the reliability of paleoenvironmental reconstruction results. *Quaternary International* 562 (2020) 85 – 93. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85088219044&doi=10.1016%2fj.quaint.2020.07.005&partnerID=40&md5=bf3f6d1e466516f1b03d1a453a671464>. doi:10.1016/j.quaint.2020.07.005.
- [150] L. Xingfeng, L. Yuqiu, Z. Ying, X. Yongxin, C. Jian, W. Guiyi, C. Yuguang. Research on fracture toughness of x80 pipeline girth welds based on quantitative assessment of fractal characteristics of fracture surfaces. *Theoretical and Applied Fracture Mechanics* 139 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105010947763&doi=10.1016%2fj.tafmec.2025.105098&partnerID=40&md5=40977d97630da827b135ad522bcd3f4b>. doi:10.1016/j.tafmec.2025.105098.
- [151] Y. Ma, Z. Ji, W. Yang, L. Li, L. Han, Y. Liu, Y. Guo, A. A. Dmytriw, C. He, G. Li, H. Zhang. Role of optical coherence tomography in pipeline embolization device for the treatment of vertebral-basilar artery dissecting aneurysms. *Journal of NeuroInterventional Surgery* 16 (2023) 308 – 312. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85152739813&doi=10.1136%2fjnis-2022-019927&partnerID=40&md5=bec94c6bd749cb6ced397281c624e421>. doi:10.1136/jnis-2022-019927.
- [152] J. D. Stets, A. Dal Corso, J. B. Nielsen, R. A. Lyngby, S. H. N. Jensen, J. Wilm, M. B. Doest, C. Gundlach, E. R. Eiriksson, K. Conradsen, A. B. Dahl, J. A. Bærentzen, J. R. Frisvad, H. Aanes. Scene reassembly after multimodal digitization and pipeline evaluation using photorealistic rendering. *Applied Optics* 56 (2017) 7679 – 7690. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85029805318&doi=10.1364%2fao.56.007679&partnerID=40&md5=413a0c733a6319a3c7f657cecdc2ad4c>. doi:10.1364/AO.56.007679.
- [153] S. Song, Y. Li, Z. Li, Z. Hu, S. Li, G. R. Cho, J.-H. Li, volume 52, p. 175 – 180. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85079681247&doi=10.1016%2fj.ifacol.2019.12.303&partnerID=40&md5=4748f82f14737ea7f8c6f563b8c24068>. doi:10.1016/j.ifacol.2019.12.303.
- [154] M. Guo, X. Liang, Y. Zhao, G. Wang, K. Guo. Seismic deformation analysis of precast concrete pipe hybrid based on 3d lidar and unmanned aerial vehicle photogrammetry. *Sensors and Materials* 36 (2024) 3025 – 3045. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85201082923&doi=10.18494%2fSAM5076&partnerID=40&md5=e8412c539066f84c1952c24bf748d103>. doi:10.18494/SAM5076.



- [155] N. Senior, P. Boisvert, A. Runstedtler, M. Arafin. Simulating liquid pipeline flow using the rotating cage method. NACE - International Corrosion Conference Series 2015-January (2015). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84940526068&partnerID=40&md5=2ac5a3f8d37a8065fdf45e6d567087f6>.
- [156] F. Cavedo, M. Norgia, A. Pesatori, G. E. Solari. Steel pipe measurement system based on laser rangefinder. IEEE Transactions on Instrumentation and Measurement 65 (2016) 1472 – 1477. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84960172607&doi=10.1109/2fTIM.2016.2514758&partnerID=40&md5=fe1b4de9966a47a1efedc1452c8ad763>. doi:10.1109/TIM.2016.2514758.
- [157] R. Kaufmann, E. Fagerholt, V. Aune, p. 23 – 28. URL: [https://www.scopus.com/inward/record.uri?eid=2-s2.0-85125409830&doi=10.1007/2f978-3-030-86745-4\\_3&partnerID=40&md5=2eb3088b33986008cd39fb5cd8ec94b2](https://www.scopus.com/inward/record.uri?eid=2-s2.0-85125409830&doi=10.1007/2f978-3-030-86745-4_3&partnerID=40&md5=2eb3088b33986008cd39fb5cd8ec94b2). doi:10.1007/978-3-030-86745-4\_3.
- [158] P. N. Silva, G. Svenningsen, A. Dugstad, J. A. C. P. Gomes. The effect of oxygen on the co2 corrosion of tensile wires in simulated annulus environments of flexible pipes. Materials and Corrosion 73 (2022) 669 – 686. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85123491428&doi=10.1002/2fmaco.202112787&partnerID=40&md5=157259b4b9d285fa3acec14cce4011a2>. doi:10.1002/maco.202112787.
- [159] T. C. Truong, J.-R. Lee. Thickness reconstruction of nuclear power plant pipes with flow-accelerated corrosion damage using laser ultrasonic wavenumber imaging. Structural Health Monitoring 17 (2018) 255 – 265. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85032445702&doi=10.1177/2f1475921716689733&partnerID=40&md5=201b0d038cf5fc607636da8864c9dc6c>. doi:10.1177/1475921716689733.
- [160] F. Yu, J. Chen, Q. Tao, C. Su. Three-dimensional phase interface reconstruction of micro-grooved heat pipe based on optical sectioning microscopy. Micro-gravity Science and Technology 35 (2023). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85158027389&doi=10.1007/2fs12217-023-10050-3&partnerID=40&md5=e89754cdfac6efcfb90c9d3fed6e1d3>. doi:10.1007/s12217-023-10050-3.
- [161] Z. Belarbi, B. George, N. Moradighadi, D. Young, S. Nescic, M. Singer, R. Nogueira. Volatile corrosion inhibitor for prevention of black powder in sales gas pipelines. NACE - International Corrosion Conference Series 2018-April (2018). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85053515340&partnerID=40&md5=fb78096d250972bcd2c5fb616f81fd87>.
- [162] Z. Wang, X. Hu, S. Zhang, L. Qiu, Y. Lin, L. Li, Y. Xiang, J. Li. Federated split learning-driven multimodal physical-virtual integration framework: High-fidelity full-cross-section deformation field reconstruction in precise metal tube bending manufacturing (2025). doi:10.2139/ssrn.5277159.
- [163] J. Gao, H. Zhang, J. Sun, Q. Wang. Research on the resolution improvement method of multi-slit streak tube imaging based on compression sensing (2024). doi:10.2139/ssrn.4988888.
- [164] J. Jiao, P. Zhang, M. Y. Tan. Mechanism-informed 3d analysis of fracture surfaces in hydrogen-charged line pipe steels (2025). doi:10.2139/ssrn.5390989.
- [165] J. Wang, C. Wang, Y. Liu, X. Zhang, J. Huang. Detection and effectiveness of improved drainage pipe defects-based semantic segmentation labeling methods. Journal of Pipeline Systems Engineering and Practice 16 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105009827169&doi=10.1061/2fJPSEA2.PSENG-1898&partnerID=40&md5=1dfa3a2dbef4ab72f19737a9e4a5edc1>. doi:10.1061/JPSEA2.PSENG-1898.
- [166] Y. J. Lu, C. Wang. Application of one point clustering algorithms to develop a defect comparison model for differential time inspection of chemical pipelines. Journal of Loss Prevention in the Process Industries 97 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105007304824&doi=10.1016/2fj.jlp.2025.105701&partnerID=40&md5=45570c88acf0c184ee1dcf6765d2f4d6>. doi:10.1016/j.jlp.2025.105701.
- [167] L. Yang, J. Zhao, Z. Wang, Y. Liu, D. Chi. M-kanunet: enhanced defect segmentation in x-ray images of copper pipe welds via multi-scale representation and kolmogorov-arnold networks. Visual Computer 41 (2025) 7201 – 7214. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85217650541&doi=10.1007/2fs00371-025-03800-4&partnerID=40&md5=00eb8ef3fb8499e52ec53abe8f47ca38>. doi:10.1007/s00371-025-03800-4.
- [168] Q. Jin, Q. Han, J. Qian, L. Sun, K. Ge, J. Xia. Drainage pipeline multi-defect segmentation assisted by multiple attention for sonar images. Applied Sciences (Switzerland) 15 (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85215690567&doi=10.3390/2fapp15020597&partnerID=40&md5=434ec4a579cbee40c98b598a8dfc6cbb>. doi:10.3390/app15020597.
- [169] K. Guan, Y. Zhou, L. Wang, B. Chang, D. Du. A self-configuring transformer segmentation method for welding radiographic defect detection in steel pipes. Nondestructive Testing and Evaluation (2025). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-105002652457&doi=10.1080/2f10589759.2025.2491739&partnerID=40&md5=2880c0c90815121f8e4b4561bc2d83f1>. doi:10.1080/10589759.2025.2491739.
- [170] W. Shen, J. Zhang, Y. Zheng, X. Zhou, A. Song, pp. 64 – 70. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85203182155&doi=10.1145/2f3674746.3674781&partnerID=40&md5=02f1332744169d2da15ba7d7525192ff>. doi:10.1145/3674746.3674781.
- [171] K. Song, H. Feng, T. Cao, W. Cui, Y. Yan. Mfanet: Multifeature aggregation network for cross-granularity few-shot seamless steel tubes surface defect segmentation. IEEE Transactions on Industrial Informatics 20 (2024) 9725 – 9735. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85191230014&doi=10.1109/2fTII.2024.3383513&partnerID=40&md5=0ce04a029800f6aa2aff266e6231670b>. doi:10.1109/TII.2024.3383513.
- [172] O. Álvarez Tuñón, L. Ribeiro Marnet, M. Aubard, L. Antal, M. Costa, Y. Brodskiy. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85206494266&doi=10.1109/2fOCEANS51537.2024.10682150&partnerID=40&md5=45d8de465a742d94a15d498b52bac764>. doi:10.1109/OCEANS51537.2024.10682150.
- [173] E. M. Paul, G. J. Prabhu, B. Perumal, T. Senthil, M. Suresh Chinnathampy, T. Jarin. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85191686722&doi=10.1109/2fESCI59607.2024.10497365&partnerID=40&md5=a0be5e17a44ee540b3f3d2f38cc529e4>. doi:10.1109/ESCI59607.2024.10497365.
- [174] A. Behbahanian, A. A. Belanger, R. Coelman, R. Dalfonso, R. Lundstrom. A novel approach to pipeline feature identification using semantic segmentation (2024) 101 – 113. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85185889545&doi=10.52202/2f072781-0006&partnerID=40&md5=6d5e5ff13b035c0358a10cd4febbda15>. doi:10.52202/072781-0006.
- [175] J. Enes, R. R. Expósito, J. Fuentes, J. L. Cacheiro, J. Touriño. A pipeline architecture for feature-based unsupervised clustering using multivariate time series from hpc jobs. Information Fusion 93 (2023) 1 – 20. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85144624363&doi=10.1016/2fj.inffus.2022.12.017&partnerID=40&md5=5e40171b6b3557c807b5fd2d8bce81c2>. doi:10.1016/j.inffus.2022.12.017.
- [176] X. Yang, D. Xia, T. Kin, T. Igarashi. A two-step surface-based 3d deep learning pipeline for segmentation of intracranial aneurysms. Computational Visual Media 9 (2023) 57 – 69. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85140223659&doi=10.1007/2fs41095-022-0270-z&partnerID=40&md5=2e4f6d2997a3e097f89fa89a44f36166>. doi:10.1007/s41095-022-0270-z.

- [177] H. Chu, R. Cao, L. Deng, pp. 2406 – 2413. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85160319221&doi=10.1201/2F9781003348030-289&partnerID=40&md5=f5d6f5910615e371c4cf8a69a6b5da83>. doi:10.1201/9781003348030-289.
- [178] J. Kim, J. Park, G. C. Cho, S. Shim, pp. 2446 – 2454. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85160329997&doi=10.1201/2F9781003348030-294&partnerID=40&md5=495521dde28e13b19c2bb03f50fcb7d5>. doi:10.1201/9781003348030-294.
- [179] Q. Ji, J. Wu, D. Kong, L. Zhang, C. Hou, volume 12610. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85158948461&doi=10.1117/2F12.2671252&partnerID=40&md5=b05de7075d0cb95a701f701bc9021105>. doi:10.1117/12.2671252.
- [180] Y. Zhou, L. Zhu, D. Ma, volume 2639. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85179501977&doi=10.1088/2F1742-6596/2F2639/2F1/2F012057&partnerID=40&md5=94a8eed6ffcd8103248ab440338b5818>. doi:10.1088/1742-6596/2639/1/012057.
- [181] Z. Wang, Z. Liu. Mem-rcnn: A deep learning based image segmentation algorithm for pipeline magnetic leakage defects (2023) 202 – 205. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85186743633&doi=10.1109/2FICN60549.2023.10425796&partnerID=40&md5=7ee2d2e56848b36f3bbe24c918f7cfba>. doi:10.1109/ICN60549.2023.10425796.
- [182] V. A. Golodov, A. A. Maltseva. Approach to weld segmentation and defect classification in radiographic images of pipe welds. NDT and E International 127 (2022). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85122502573&doi=10.1016/2Fj.ndteint.2021.102597&partnerID=40&md5=631c0116d6ea67a9b12f02b3ea422692>. doi:10.1016/j.ndteint.2021.102597.
- [183] D. Feng, X. Wang, H. Zhang, J. Yang, Z. Yuan, L. Zhang, J. Liu, B. Zhang. Attribute recognition of buried pipes based on multi-trace phase features using k-means clustering for gpr data interpretation. Journal of Environmental and Engineering Geophysics 26 (2021) 117 – 132. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85109509883&doi=10.32389/2Fjeeg20-030&partnerID=40&md5=5e9e97eff1e53b5fc1b41d96fe80771>. doi:10.32389/jeeg20-030.
- [184] C. K. Groschner, C. Choi, M. C. Scott. Machine learning pipeline for segmentation and defect identification from high-resolution transmission electron microscopy data. Microscopy and Microanalysis 27 (2021) 549 – 556. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85105458009&doi=10.1017/2F1431927621000386&partnerID=40&md5=d502a9e0ca6e415f5f8a07a1de17924b>. doi:10.1017/S1431927621000386.
- [185] L. Zöllei, J. E. Iglesias, Y. Ou, P. E. Grant, B. R. Fischl. Infant freesurfer: An automated segmentation and surface extraction pipeline for t1-weighted neuroimaging data of infants 0–2 years. NeuroImage 218 (2020). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85085558787&doi=10.1016/2Fj.neuroimage.2020.116946&partnerID=40&md5=3852136dd12e6b16fb92dcadd2a323cc>. doi:10.1016/j.neuroimage.2020.116946.
- [186] R. Löuk, A. Riid, R. Pihlak, A. Tepļakov. Pavement defect segmentation in orthoframes with a pipeline of three convolutional neural networks. Algorithms 13 (2020). URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85090390206&doi=10.3390/2FA13080198&partnerID=40&md5=da42f88c0e885c7e10caf45a31b79e2b>. doi:10.3390/A13080198.
- [187] V. A. Golodov, A. A. Mittseva. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85074231761&doi=10.1109/2FRUSAUTOCON.2019.8867734&partnerID=40&md5=e43c6fd4ff730b7563a83b96df7ba977>. doi:10.1109/RUSAUTOCON.2019.8867734.
- [188] H. Ju, X. Wang, T. Zhang, Y. Zhao, Z. Ullah, volume 2019-June, pp. 694 – 699. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85082011189&doi=10.1109/2FPIERS-Spring46901.2019.9017529&partnerID=40&md5=6111f7e8a94e87951e69ff4f946558e8>. doi:10.1109/PIERS-Spring46901.2019.9017529.
- [189] S. Zhao, H. Huang. Deep learning-based instance segmentation for water leakage defects of metro shield tunnel (2019) 3475 – 3482. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85068382581&doi=10.1201/2F9780429424441-368&partnerID=40&md5=c294b7229f019991bc364436a33d41c9>. doi:10.1201/9780429424441-368.
- [190] M. Wang, J. C. Cheng, pp. 586 – 594. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85071434510&doi=10.22260/2Fisarc2019/2F0078&partnerID=40&md5=5638a1fb514560ad08a9a62ec262b253>. doi:10.22260/isarc2019/0078.
- [191] J. Liu, Y. Ma, H. Zhang, H. Su, G. Xiao. A modified fuzzy min–max neural network for data clustering and its application on pipeline internal inspection data. Neurocomputing 238 (2017) 56 – 66. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85012267388&doi=10.1016/2Fj.neucom.2017.01.036&partnerID=40&md5=8438db6b1b0e536a9388be7f444d1bf8>. doi:10.1016/j.neucom.2017.01.036.
- [192] B. Sahu, S. N. Dehuri, A. K. Jagadev. Feature selection model based on clustering and ranking in pipeline for microarray data. Informatics in Medicine Unlocked 9 (2017) 107 – 122. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85029693955&doi=10.1016/2Fj.imu.2017.07.004&partnerID=40&md5=d18fdb0e31b0a049c3a0c73973fbc23f>. doi:10.1016/j.imu.2017.07.004.
- [193] J. Du, R. He, V. Sugumaran. Clustering and ontology-based information integration framework for surface subsidence risk mitigation in underground tunnels. Cluster Computing 19 (2016) 2001 – 2014. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84988695184&doi=10.1007/2F10586-016-0631-4&partnerID=40&md5=0cc80059656d4ad454bf3b1a4a00d230>. doi:10.1007/s10586-016-0631-4.
- [194] Y. Ma, J. Liu, Z. Wang, volume 2016-August, pp. 3509 – 3513. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84987924512&doi=10.1109/2FChiCC.2016.7553898&partnerID=40&md5=af86ee1246d77e9a2ce7164e210b2487>. doi:10.1109/ChiCC.2016.7553898.
- [195] H. Wang, A. Yajima, R. Y. Liang, H. Castaneda. A bayesian model framework for calibrating ultrasonic in-line inspection data and estimating actual external corrosion depth in buried pipeline utilizing a clustering technique. Structural Safety 54 (2015) 19 – 31. URL: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84922368290&doi=10.1016/2Fj.strusafe.2015.01.003&partnerID=40&md5=f433934c7f43470f54bcd149a22cf3cf>. doi:10.1016/j.strusafe.2015.01.003.
- [196] Y. Mai, Z. Zhang, X. Zhou, Y. Sun, Q. Xin. Point-mfan: A multi-feature attention network for point cloud segmentation of urban underground pipes (2025). doi:10.2139/ssrn.5179918.
- [197] C. Mei, P. Rives, in: Proceedings 2007 IEEE International Conference on Robotics and Automation, pp. 3945–3950. doi:10.1109/ROBOT.2007.364084.
- [198] V. Usenko, N. Demmel, D. Cremers, in: 2018 International Conference on 3D Vision (3DV), IEEE, 2018. URL: <http://dx.doi.org/10.1109/3DV.2018.00069>. doi:10.1109/3dv.2018.00069.
- [199] D. Scaramuzza, A. Martinelli, R. Siegwart, in: Fourth IEEE International Conference on Computer Vision Systems (ICVS'06), IEEE, 2006. doi:10.1109/icvs.2006.3.
- [200] Y. Liu, F. Zhou, W. Zhang, L. Yang, Z. Guo, H. Tan. Flexible calibration method for a quad-directional stereo vision sensor based on unconstrained 3-d target. IEEE Sensors Journal 24 (2024) 3499–3512. doi:10.1109/jsen.2023.3344594.



## APPENDIX A: LITERATURE REVIEW

Table A.1: 2024 metrics for journals which contributed more than one item to the search space.

| Source                                                                   | CS   | SJR   | SNIP  | Studies              |
|--------------------------------------------------------------------------|------|-------|-------|----------------------|
| IEEE Sensors Journal                                                     | 8.2  | 1.039 | 1.495 | [12, 14, 32, 57, 85] |
| Automation in Construction                                               | 20.9 | 2.890 | 3.448 | [22, 34, 35, 43, 86] |
| Tunneling and Underground Space Technology                               | 13.0 | 2.269 | 2.533 | [1, 44, 48]          |
| Sensors                                                                  | 8.2  | 0.764 | 1.312 | [33, 45, 87]         |
| Measurement Science and Technology                                       | 4.4  | 0.585 | 1.057 | [16, 39, 88]         |
| Journal of Nondestructive Evaluation                                     | 4.5  | 0.568 | 1.089 | [19, 29, 89]         |
| IEEE Access                                                              | 9.0  | 0.849 | 1.504 | [40, 90, 91]         |
| Wear                                                                     | 10.4 | 1.204 | 1.800 | [92, 93]             |
| Signal Image and Video Processing                                        | 4.0  | 0.523 | 0.939 | [55, 94]             |
| Materials Characterization                                               | 8.2  | 1.338 | 1.482 | [95, 96]             |
| Materials                                                                | 6.4  | 0.614 | 0.996 | [97, 98]             |
| International Journal of Pattern Recognition and Artificial Intelligence | 2.5  | 0.273 | 0.404 | [99, 100]            |
| Engineering Failure Analysis                                             | 8.8  | 1.159 | 1.865 | [101, 102]           |
| Construction and Building Materials                                      | 13.9 | 2.094 | 2.084 | [47, 103]            |
| Computer Aided Civil and Infrastructure Engineering                      | 17.4 | 3.012 | 2.961 | [36, 42]             |

Table A.2: Snowball results.

| Cite  | Inclusion reason                                                                                    | From |
|-------|-----------------------------------------------------------------------------------------------------|------|
| [24]  | Foundational camera calibration method. Has 3474 citations and a FWCI of 28.37.                     | [55] |
| [56]  | Basis method for fisheye lenses, used by OpenCV [104]. Has 813 citations and a FWCI of 9.74.        | [54] |
| [18]  | Laser profile based pipe reconstruction. Has 59 citations and a FWCI of 3.68.                       | [16] |
| [105] | Optical in pipe inspection. Has 15 citations and an FWCI of 1.51.                                   | [12] |
| [21]  | Laser scan pipe inspection. Has 28 citations and a FWCI of 3.29.                                    | [16] |
| [68]  | Circular gauge reconstruction and camera to laser calibration. Has 25 citations and a FWCI of 1.69. | [16] |
| [28]  | Projection based internal pipe inspection. Has 15 citations and a FWCI of 0.94.                     | [16] |
| [106] | Pipeline inspection and segmentation . Has 5 citations and a FWCI of 2.37.                          | [22] |
| [59]  | Tunnel point cloud segmentation. Has 21 citations and a FWCI of 2.13.                               | [22] |
| [23]  | Sewer point cloud segmentation. Has 76 citations and a FWCI of 5.20.                                | [21] |

Table A.3: Summary of all 17 Scopus papers with inclusion or exclusion decisions and justifications related to camera calibration.

| Cite  | Summary                                                                                                                                                                                                                                                 | Meets     |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| [107] | CNN + SfM to learn fisheye lens aberration. <b>Supervised self calibration using deep learning and SfM.</b>                                                                                                                                             | 1a = N    |
| [90]  | GAN to generate synthetic datasets of fisheye and pipeline distorted images. <b>Generates synthetic datasets of fisheye distorted images in pipelines.</b>                                                                                              | 2a = N    |
| [108] | Development of calibration tool and method using the custom target. <b>Custom hardware tool and target for fisheye lens calibration.</b>                                                                                                                | 1a = N    |
| [54]  | Layered refraction model for fisheye calibration in a watertight dome. <b>Fish eye camera calibration and refraction modeling. Applied underwater</b>                                                                                                   | 1a;2a = Y |
| [109] | Pose estimation between LiDAR a fisheye lens. <b>LiDAR dependent camera calibration.</b>                                                                                                                                                                | 1a = N    |
| [110] | Multi camera calibration using Self-Calibration Bundle Adjustment and SfM reconstruction. <b>Relative multi camera calibration.</b>                                                                                                                     | 1a;1b = N |
| [55]  | Real time fish eye image correction using an overall correction, image stitching with cross features. <b>Fish eye camera calibration, image stitching. Applied underwater.</b>                                                                          | 1a;2a = Y |
| [88]  | Calibrates underwater fisheye cameras by modeling how light bends through water and the fisheye lens using the light field using a wave technique. <b>Multi-frequency heterodyne fisheye lens calibration underwater.</b>                               | 1a;2a = Y |
| [111] | Self supervised CNN for learning depth in distorted images. <b>Use rich textures for self supervised depth learning.</b>                                                                                                                                | 1a = N    |
| [112] | Spherical perspective projection for fish eye images. Straight lines in 3D space are not forced to be straight in the image, but become circles on a sphere. <b>Spherical perspective projection constraint for undistortion.</b>                       | 1a;2b = Y |
| [113] | Rotating sphere model for fisheye image undistortion. <b>Fisheye image undistortion. Applied underwater</b>                                                                                                                                             | 1a;2a = Y |
| [114] | YOLOv4 based post processing of fisheye images to correct bounding box centers. <b>Post-processing of bounding box center coordinates to reduce classification errors in fisheye images.</b>                                                            | None = N  |
| [115] | Fisheye image correction using latitude-longitude mapping, spherical projection, and panoramic stitching concepts to detect the image center and radius. <b>Through CHT and a hybrid of 3 other correction methods fisheye images are undistorted.</b>  | 1a;2b = Y |
| [116] | 3D metric map computation and obstacle detection for application in self driving cars. Calibrates multi cam setup using SLAM without a target. <b>Calibration of multi-camera fisheye system</b>                                                        | 1a = N    |
| [117] | Multi camera system underwater calibration. <b>Full text not available under UTwente license.</b>                                                                                                                                                       | 2a = N    |
| [118] | Multi camera calibration using lane lines and stitched image features from driving videos to estimate poses. <b>Multi camera system image stitching and road line based calibration.</b>                                                                | 1a = N    |
| [119] | Stereoscopic calibration box based fish eye lens calibration using a convex polygon algorithm, circle center, and an adaptive maximum extra planar inscribed model. <b>Using a custom 3D reference box calibration is performed in fish eye lenses.</b> | 1a = N    |

Table A.4: Summary of all 68 Scopus papers with inclusion or exclusion decisions and justifications related to reconstruction.

| Cite  | Summary                                                                                                                                                                                                                                                                     | Meets        |
|-------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------|
| [12]  | Laser profiling using a conic mirror and 3D reconstruction. Laser extraction using skeleton binarization and center detection. Result is meshed using MeshLab. Curvature is used to color the mesh. <b>3D reconstruction and laser profiling.</b>                           | 1b;2a = Y    |
| [13]  | Simulation of laser profiling using and 3D reconstruction. <b>Models (so no real data) a pipeline and inspection robot for 3D reconstruction of the pipeline.</b>                                                                                                           | 1b;2a = Y    |
| [4]   | Ambient lit optical flow based 3D reconstruction using a circular coordinate system. <b>Using real data performs 3D reconstruction and velocity estimation.</b>                                                                                                             | 1a;2a = Y    |
| [120] | Single frame 3D reconstruction method for pipe diameter measurement. Uses MIVOS to isolate the pipeline and remove background noise. Uses RANSAC cylinder fit for optimization. <b>Depth camera based 3D reconstruction.</b>                                                | 1b = N       |
| [121] | Preprocessing of point clouds for plant surface reconstruction. <b>Preprocesses point clouds for plant surface reconstruction.</b>                                                                                                                                          | None = N     |
| [14]  | Optical laser system to create a 3D reconstruction of the pipeline. Laser plane calibration, centerline extraction and 3D reconstruction is done by known movement. <b>Laser aided optical calibration, reconstruction of various different pipelines.</b>                  | 1a;1b;2a = Y |
| [122] | Evaluates high temperature wear performance of various composite claddings. <b>Material science</b>                                                                                                                                                                         | None = N     |
| [123] | Evaluates point cloud data without a ground truth model by using architectural constraints. Checks the internal consistency of walls (perpendicularity, parallelism and thickness). <b>Focuses on reconstruction evaluation if no ground truth is present.</b>              | None = N     |
| [124] | Analyze corrosion fields on buried pipelines using wavelet transforms. Generate synthetic corrosion fields that match key statistical and structural properties of real corrosion data. <b>Generate corrosion fields that statistically resemble the original.</b>          | 2a = N       |
| [125] | Image processing for measuring the number, location and composition of drusen-like deposits. Works by using high throughput confocal microscopy and 3D reconstruction. <b>Measuring and counting pipeline for drusen-like deposits.</b>                                     | None = N     |
| [126] | Matches external outer contour detection masks across images for 3D axis reconstruction of pipes. The 3D reconstruction is adjusted further to get a more accurate reconstruction. <b>Reconstructs specific pipeline items for use in CAD software.</b>                     | 1b;1c = N    |
| [127] | Aims to detect the maximum heat transfer a heat pipe can achieve by investigating the capillary layer which is deposited on the walls. <b>Material science paper which experimentally measures heat transfer.</b>                                                           | None = N     |
| [93]  | Pretting experiments cylindrical pads to asses wear damage and formation of tribo particles. <b>Material science.</b>                                                                                                                                                       | None = N     |
| [128] | Polishes the sidewalls and evaluates using profilometry. <b>Material science and not available under UTwente license.</b>                                                                                                                                                   | None = N     |
| [129] | Proposes a new method for creating an electrode. <b>Electrochemical science.</b>                                                                                                                                                                                            | None = N     |
| [130] | Data reduction for Magneto Optical Filter based synoptic solar telescopes. <b>Data reduction procedures for MOF based telescopes.</b>                                                                                                                                       | None = N     |
| [96]  | Takes samples from steel pipes, treats them thermomechanically and then exposes them to controlled corrosive environments. Mapped microstructural changed and retrieved 3D optical profilometry. <b>Material science.</b>                                                   | 2a = N       |
| [131] | Analyzes and reconstructs the corrosion on external surfaces of steel pipelines. Uses various wavelet functions to analyze the corrosion. <b>Using external pipeline data analyzes corrosion.</b>                                                                           | 2a = N       |
| [132] | Coded exposure pixel image sensor which allows for each pixel to collect light. This results in a single pictures being able to capture detailed 3D shape and surface information from a single frame. <b>New design for a sensor for 3D depth and surface information.</b> | 1b = N       |
| [133] | Captures 4D facial expressions for optical flow. Uses artist-designed templates to keep the mesh structure consistent while matching shape and appearance. <b>Reconstruction of face meshes using cameras.</b>                                                              | None = N     |
| [134] | Tests a micro heat pipe design with extra fluid to improve cooling of electronic components. Compares performance with and without excess liquid to see how it affects heat transfer in different pipe zones. <b>Material science related to heat transfer.</b>             | None = N     |
| [102] | Investigates why a radiant tube in an ethylene cracking unit failed early. Analysis showed that thermal shocks from unexpected shutdowns caused stress and chromium loss, leading to the tube's failure. <b>Failure analysis study in material science.</b>                 | None = N     |
| [135] | Introduces how structured light scanners are used in forensic work in Zurich to document bodies and objects. <b>Explains the scanning workflow, communication process, and how the data helps in reconstructing incidents.</b>                                              | None = N     |
| [136] | Analyzes how 3D-printed metal tubes break apart under extreme strain. Combines X-ray tomography and imaging to link fragmentation patterns to material porosity, tube size, and impact speed. <b>Material properties of 3D-printed metal tubes under strain.</b>            | None = N     |
| [137] | Studies the effects of flow and impurities on corrosion in carbon steel pipelines. <b>Study about material performance. Not accessible with UTwente license.</b>                                                                                                            | None = N     |
| [138] | Tested a single microfocus X-ray setup for 2D and 3D breast imaging using in-line phase contrast methods. <b>Biomedical study aiming to improve image quality and microcalcification visibility.</b>                                                                        | None = N     |

Continued on next page

| Cite  | Summary                                                                                                                                                                                                                                                                     | Meets        |
|-------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------|
| [19]  | Laser-aided optical pipeline imaging for defect classification using CNN/LSTM models and hierarchical bilinear pooling. <b>Collects laser ring data from the innards of gas pipelines and segments defects. Does not do reconstruction.</b>                                 | 1c;2a = Y    |
| [139] | Proposes a pipe scanning system that uses two omnidirectional mirrors and a laser to reconstruct the inner 3D profile of small pipes with further development for ear canals. <b>Not available under UTwente licence.</b>                                                   | 1b;2a = N    |
| [95]  | measures how austenite grains grow in X80 pipeline steel during heating. Two in-situ techniques were used to track average grain size and grain surface changes. <b>Study of grain growth in metallurgy</b>                                                                 | None = N     |
| [140] | Smooths the inner surface of laser-welded stainless steel pipes and uses profilograms to asses material properties. <b>Take profilograms of the laminated inner surface and dicuss material properties.</b>                                                                 | 2a = N       |
| [141] | Developed a microfabrication pipeline to create custom cell culture devices. <b>Pipeline for microfabrication.</b>                                                                                                                                                          | None = N     |
| [142] | Studied effects of a magnetic field on the coating of inner surfaces in tubes. <b>Magnetic-field-assisted coating inside tubes.</b>                                                                                                                                         | None = N     |
| [143] | Non-intrusive method for measuring sound pressure distribution inside a tube to capture projections and filtered back-projection to reconstruct the sound field <b>Measure sound pressure distribution using an optical method.</b>                                         | None = N     |
| [98]  | Evaluated thin-walled cooling pipes using multiple structural and compositional analysis techniques. <b>Analyses the microstructure and mechanical properties of pipes. Material science and not full scale pipeline geometry.</b>                                          | 2a = N       |
| [15]  | 3D reconstruction of a pipe interior by projecting laser points using contour detection and fitting. <b>Reconstructs pipe inner surface using laser points and contour detection. Also includes calibration methodology.</b>                                                | 1a;1b;2a = Y |
| [144] | Studies various methods for reconstructing external 3D shapes and positions of buried pipes. Estimates the central axis of point clouds and fits a standardized pipe model. <b>External 3D pipe reconstruction and position location.</b>                                   | 1b = N       |
| [57]  | Multisensor system for the reconstruction of pipeline interiors. R3LIVE is used to integrate LiDAR, RGB cameras and an Inertia Measurement Unit. <b>3D reconstruction of pipeline interiors using multisensor fusion and deep learning.</b>                                 | 1b;2a = Y    |
| [145] | Analyses the amino acid composition of tube silk from Ariadna spiders in the Namib desert. The analysis of the silk was done with mass spectrometry, FTIR and DSC. <b>Analyses structural and thermal properties of spider silk.</b>                                        | None = N     |
| [146] | Registration of 3D surface scans invariant to translation, rotation and uniform scaling. Edges are detected and clustered to segment contours, while mesh decimation reduces complexity. <b>3D scan registration method.</b>                                                | None = N     |
| [86]  | Converts 3D point clouds into building information models in IFC format by segmenting walls, slabs and other geometric features. This is done using 2D projection and clustering and fitting geometry. <b>Converts point clouds into building information models.</b>       | 1c = N       |
| [147] | Studies how heat moves through porous materials in flat micro heat pipes by measuring surfaces using lasers. <b>Material science</b>                                                                                                                                        | None = N     |
| [16]  | 3D interior pipeline measuring system using a robot and a multi-directional structured light sensor which uses a single camera and a pyramid mirror to capture various line stripes. <b>3D pipeline interior reconstruction by line stripe capture and contour fitting.</b> | 1a;1b;2a = Y |
| [148] | Created highly reflective coatings on flat silica tubes. <b>Material science.</b>                                                                                                                                                                                           | None = N     |
| [149] | Examined calcareous root tubes from the Tengger desert to see if recrystallization affects their reliability for paleoenvironmental studies. <b>Geochemical analysis and paleoclimatology.</b>                                                                              | None = N     |
| [150] | Measure fracture toughness of different zones of a pipeline weld using bending tests, a 3D reconstruction was made using laser scanning. The reconstruction was analyzed through fractal analysis on the surface topology. <b>Material science.</b>                         | None = N     |
| [20]  | Small pipe interior is scanned using a 360 degree laser sensor which results in a 3D point cloud. This is then converted into a surface model using Poisson surface reconstruction. <b>Pipeline interior scanning and reconstruction from a 3D point cloud.</b>             | 1b;2a = Y    |
| [100] | Uses a path planning algorithm for a spraying robot using a laser displacement sensor to scan pipe interiors. Pre-scans various cross-section shapes to build accurate models while avoiding collisions during measurement. <b>Not available under UTwente license.</b>     | 1b;2a = N    |
| [151] | Using optical coherence tomography, MRI and DSA they check neointima growth on a flow diverter over various time periods. <b>Research about neointima growth on a flow diverter using various methods.</b>                                                                  | None = N     |
| [152] | Multimodal 3D scanning pipeline for scenes with both transparent and regular objects. <b>Multimodal imaging and 3D reconstruction of transparent objects in a scene.</b>                                                                                                    | 1b = N       |
| [153] | Used 2D forward looking sonar to create 3D maps of the seabed. Stitched the results into a full terrain map with a point cloud registration method. <b>Converted 2D sonar data into a 3D seabed surface map using shape-from-shading and stitching.</b>                     | 2a = N       |
| [154] | 3D LiDAR + aerial photos for reinforced concrete hybrid frame deformation testing using SfM and Delaunay surface reconstruction. <b>Uses SfM to build a 3D model of concrete frames.</b>                                                                                    | 1b = N       |
| [155] | studied how liquids flow in pipelines using a method called the rotating cage. <b>Simulated how various factors affected the flow of fluids in pipelines and stress on the walls.</b>                                                                                       | 2a = N       |
| [92]  | Tested various cobalt based coatings for material wear. <b>Material science.</b>                                                                                                                                                                                            | None = N     |
| [58]  | Built a full pipeline from extracting the laser stripe in underwater images using a transformer based NN which from which a 3D reconstruction is made. <b>3D reconstruction of the seabed floor using 2D images where laser lines are extracted.</b>                        | 1b;2a = Y    |
| [156] | Designed an optical distance sensor which uses active triangulation. <b>Design of a optical laser sensor for distances within a pipe.</b>                                                                                                                                   | 2a = N       |
| [101] | Researches the fracture behavior of pipeline steel under various stress states. <b>Material science.</b>                                                                                                                                                                    | None = N     |
| [157] | Uses optical methods to measure how a steel plate bent when hit by shock waves and then used these deformations to reconstruct the full pressure distribution over time. <b>Material science.</b>                                                                           | None = N     |
| [158] | Researches the corrosion rate of carbon steel wires. <b>Material science.</b>                                                                                                                                                                                               | None = N     |
| [159] | Measures the flow accelerated corrosion damage in pipelines. This damage is assessed using the Ultrasonic Wavenumber Imaging. <b>Thickness reconstruction of a pipeline using Ultrasonic Wavenumber Imaging</b>                                                             | 2a = N       |
| [160] | Used optical microscopy to visualize the 3D shape of the vapor-liquid interface inside micro-grooved heat pipes and how it changes under various heat loads. Studied how various factors affect liquid distribution . <b>Material science.</b>                              | None = N     |
| [17]  | Uses LiDAR, visual and inertial sensor combined with a ring shaped laser profiler to inspect the innards of a pipe. SLAM is used for 3D reconstruction. <b>Pipeline interior reconstruction using various sensors and SLAM.</b>                                             | 1b;2a = Y    |
| [161] | Tested variuos volatile corrosion inhibitors to see how well it prevented black powder formation in steel gas pipelines. <b>Study on black powder formation prevention in gas pipes.</b>                                                                                    | None = N     |
| [162] | Stereo vision 3D deformation tracking of metal tubes during bending. Uses split and federated learning for combining various data types from distributed sources for 3D reconstruction. <b>3D tube bend reconstruction based on federated learning.</b>                     | 1b = N       |
| [163] | Integrated a digital micromirror device with a multi-slit streak tube LiDAR system to sample and reconstruct intensity and range images. <b>Develops an imaging system for improving the streak image from a LiDAR system.</b>                                              | None = N     |
| [164] | Measures and analyses fracture surfaces on hydrogen charged steel <b>Material science</b>                                                                                                                                                                                   | None = N     |

Table A.5: Summary of all 70 Scopus papers with inclusion or exclusion decisions and justifications related to segmentation.

| Cite  | Summary                                                                                                                                                                                                                                                              | Meets     |
|-------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| [165] | Developed methods and guidelines for drainage pipe defects labeling. <b>Methods and guidelines for semantic segmentation labeling.</b>                                                                                                                               | 2a = N    |
| [166] | Created a clustering-based model to compare pipeline defects by combining data preprocessing (mileage calibration and weld alignment) with weighted feature clustering. <b>Clustering based defect detection and data alignment (registration) in pipelines.</b>     | 2a = N    |
| [167] | Defect segmentation of tube welds X-ray images, feature extraction with Res2Net, attention mechanisms and introducing a KAN-Transformer module to capture complex defect details. <b>Segmentation of defects in X-ray images of the casing, weld and tube areas.</b> | 2a = N    |
| [37]  | Segmentation of internal pipe images using YOLOv11-seg with a BiPANet module. <b>Pipe image defect segmentation.</b>                                                                                                                                                 | 1c;2a = Y |
| [29]  | Proposes a semi-bilateral efficient self-attention network for severity quantification of internal steel pipe surface defects. <b>Context (severity) extraction from segmented defects.</b>                                                                          | 1c;2a = Y |
| [22]  | Pipe interior point cloud segmentation. Rough segmentation using filtering and for DBSCAN + RG for finer segmentation. <b>Segments raw point cloud data with a rough segmentation and fine segmentation approach.</b>                                                | 1c;2a = Y |

Continued on next page



| Cite  | Summary                                                                                                                                                                                                                                                                  | Meets     |
|-------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| [38]  | Uses a large vision model for data annotation and an YOLOv5-based architecture for classification, localization, and segmentation of tunnel lining defects. <b>Defect detection and segmentation using a YOLOv5 based architecture on tunnel internal images.</b>        | 1c;2b = Y |
| [39]  | DeepLabV3+-based model for tunnel crack segmentation using a SwinV2 backbone, a snake convolution module and a spatial feature calibration module for feature fusion. <b>Tunnel images crack segmentation using a DeepLabV3+-based model.</b>                            | 1c;2b = Y |
| [60]  | 3D mapping system for collecting tunnel point clouds and performed segmentation using an encoder-decoder structure with self attention and neighborhood feature perception enhancement. <b>3D point cloud segmentation using an encoder-decoder structure.</b>           | 1c;2b = Y |
| [97]  | Automatic labeling and optimization algorithm for segmenting cracks in tunnel images. <b>Crack segmentation from tunnel images with deep learning.</b>                                                                                                                   | 1c;2b = Y |
| [61]  | Tunnel point cloud segmentation using a few shot learning for segmentation. Uses multi embedding networks and heterogeneous feature interaction. <b>Performs segmentation and feature extraction on tunnel point cloud data.</b>                                         | 1c;2b = Y |
| [64]  | Extracts features such as roughness and other parameters. Uses cluster results as seed point input for secondary segmentation. <b>Tunnel point cloud segmentation using clustering techniques.</b>                                                                       | 1c;2b = Y |
| [40]  | Propose a tunnel crack segmentation algorithm for tunnel images. Uses deep learning for selective feature refinement, cross-head feature sharing and multi-scale feature extraction. <b>Feature centric approach for segmenting cracks from tunnel images.</b>           | 1c;2b = Y |
| [168] | Multiple attention network for segmenting drainage pipe sonar video's. Trained on annotated data. The network is used for detection, instance segmentation and pose detection. <b>Segmentation using multiple attention network on drainage pipe sonar video's.</b>      | 1c = N    |
| [30]  | Propose a encoder-decoder structure (U-KAN) which uses Kolmogorov-Arnold Networks, Atrous Spatial Pyramid Pooling and a Edge Attention Module on internal pipe images for segmentation of defects. <b>Segment defects from internal pipe images using U-KAN.</b>         | 1c;2a = Y |
| [91]  | Segments pipelines from aerial imagery using Multi-Path Weight Convolution, Lightweight Bidirectional Feature Pyramid Network and a Multi-Level Decoupled Segmentation Head. <b>Segments pipelines and their defects from images.</b>                                    | 1c = N    |
| [169] | Segments external radiographic images of steel pipes using a self-configuring transformer-based encoder-decoder. <b>Defect segmentation of external radiographic images of steel pipes.</b>                                                                              | 1c = N    |
| [41]  | Segments defects in tunnel images using an encoder-decoder structure (Unet) with customized side guided term and various attention modules <b>Segmented defects in internal tunnel images using encoder-decoder.</b>                                                     | 1c;2b = Y |
| [42]  | Segments defects in inner tunnel images using a vision transformer with an adapter and decoding head. <b>Segmentation of internal tunnel images.</b>                                                                                                                     | 1c;2b = Y |
| [27]  | Segments defects and objects in pipe images using and adjusted DeepLabV3+. <b>Semantic segmentation of internal pipe images.</b>                                                                                                                                         | 1c;2a = Y |
| [43]  | Tunnel segmentation using a hybrid encoder tailored to band-like features and small-scale features. Design a feature pyramid-like decoder network tailored to multi-scale features. <b>Semantic segmentation of internal tunnel images.</b>                              | 1c;2b = Y |
| [44]  | Segments internal tunnel images using an integration of YOLOv8 and a Convolutional Block Attention Module (CBAM). Annotations were produced using SAM. <b>Segmentation of internal tunnel images.</b>                                                                    | 1c;2b = Y |
| [31]  | Uses a CNN and Transformer fusion network for semantic segmentation of internal pipe images. Additionally attention and a custom activation function were used. <b>Semantic segmentation of internal pipe images.</b>                                                    | 1c;2a = Y |
| [170] | Integrates YOLO feature extraction layers with ResSPP alongside with YOLACT segmentation mask generators for segmentation of pipe images. <b>Segmentation of internal pipe images.</b>                                                                                   | 1c;2a = Y |
| [89]  | Generates CT data (voxel) for AI training in a pipeline consisting of generating geometrically realistic internal defects, then generate a realistic 3D voxel representation. <b>Pipeline for generating geometrically realistic CT data for AI training purposes.</b>   | None = N  |
| [45]  | Pipe image segmentation with an encoder consisting of a residual separable convolution attention model and a decoder consisting of a global attention upsample model. <b>Performs segmentation in pipe images using an encoder-decoder architecture.</b>                 | 1c;2a = Y |
| [46]  | Crack segmentation in pipe imagery using an adjustment of YOLOv7, it adds a coordinate attention mechanism, named CA-YOLOv7. The CA-YOLOv7 is then combined with DeepLab V3+. <b>Segmentation of internal tunnel images.</b>                                             | 1c;2b = Y |
| [85]  | Segments ground-penetrating radar images using YolaTC which consists of a multi-granularity backbone, strip pooling, feature pyramid network, ProtoNet, and a detection head. <b>Ground penetrating radar images are segmented using a composite architecture.</b>       | 1c = N    |
| [171] | Uses cross-granularity FSDS which aims to learn defect segmentation on a coarse grained labeled defect dataset and generalize it to a fine grained set of labeled dataset. <b>Tackles a generalization challenge across label granularity for segmentation of tubes.</b> | 2a = N    |
| [32]  | Segments steel tube internal surface defects by pre selection (SDSNet), meta-learning-based FSDS and finally lightweight segmentation (FASNet). <b>Segmentation of internal tube images.</b>                                                                             | 1c;2a = Y |
| [172] | Provides an annotated underwater pipeline (external) inspection dataset which can be used for segmentation. <b>Provides an annotated underwater pipeline dataset.</b>                                                                                                    | None = N  |
| [173] | Proposed a method for segmenting poster anterior chest radiographs by preprocessing (median filter), GLCM feature extraction and then classification using a SVM. <b>Segments and detects Tuberculosis in poster anterior chest radiographs.</b>                         | 1c = N    |
| [1]   | Segment a disordered and sparse 3D point cloud of sewer pipe internals. This is done using an encoder-decoder architecture based on an improved PointNet++. <b>Segments a 3D point cloud of pipe internals.</b>                                                          | 1c;2a = Y |
| [174] | Segments magnetic flux leakage data using four different models. <b>Not available under UT license.</b>                                                                                                                                                                  | 1c = N    |
| [33]  | Segment pipe internal images by combining StyleGAN3 for data augmentation and Pipe-Spare-Net for segmentation (based on SparseInst). <b>Segmentation of internal tube images.</b>                                                                                        | 1c;2a = Y |
| [47]  | Segments defects in tunnel images using a context enhanced feature encoder and an atrous spatial pyramid pooling module with multiscale attention. <b>Segmentation of internal tunnel images with an encoder-decoder architecture.</b>                                   | 1c;2b = Y |
| [94]  | Proposes a segmentation method based on the integration of a bidirectional recurrent network and graph convolution network for the segmentation of tuberculosis cavity from CT scans. <b>Tuberculosis cavity segmentation in CT scans.</b>                               | 1c = N    |
| [48]  | Proposes an encoder-decoder (adjust UNet) architecture for the segmentation of internal tunnel images. <b>Segmentation of internal tunnel images with an encoder-decoder architecture.</b>                                                                               | 1c;2b = Y |
| [62]  | Proposes a method to segment defects in internal tunnel images through feature encoding, global awareness modules and a custom loss function. <b>Segmentation of internal tunnel images with an encoder-decoder architecture.</b>                                        | 1c;2b = Y |
| [87]  | Introduces sMaSDP, a simplified markerless gait event detection pipeline designed for unconstrained gait assessment using synchronous EMG and IMU data. <b>Gait assessment using a step by step method.</b>                                                              | None = N  |
| [175] | Proposes a pipeline architecture for processing and clustering multivariate time series in an unsupervised manner. <b>Big data processing.</b>                                                                                                                           | None = N  |
| [176] | Proposes a segmentation method for intracranial aneurysms from images using PointNet++ and SO-Net. <b>Intracranial aneurysms segmentation.</b>                                                                                                                           | 1c = N    |
| [177] | Multi-scale feature fusion segmentation network with an attention mechanism applied to UAV and UGV captured images in a tunnel. <b>Tunnel image segmentation.</b>                                                                                                        | 1c;2b = Y |
| [178] | Segments tunnel cracks from RGB images without deeplearning. <b>Tunnel image segmentation.</b>                                                                                                                                                                           | 1c;2b = Y |
| [179] | Using an attention based network segments defects in vaccine glass tubes. <b>Defects in vaccine glass tube segmentation.</b>                                                                                                                                             | 1c = N    |
| [180] | Segments external images of pipe defects by (iterative) thresholding, histogram bimodal, OTSU, (Sobel/Canny) edge detection, Laplacian of Gaussian, region growing, split merge regions and clustering. <b>Compares methods for segmenting external pipe images.</b>     | 1c;2b = Y |
| [181] | Uses a Mask-RCNN network for segmenting defects in magnetic flux leakage defect images. <b>Magnetic flux leakage defect image segmentation.</b>                                                                                                                          | 1c = N    |
| [34]  | Using an encoder-decoder architecture segments defects in pipes. <b>Internal pipe image segmentation.</b>                                                                                                                                                                | 1c;2a = Y |
| [182] | Segments defects in weld radiographs using various neural network architectures. <b>Weld defect segmentation.</b>                                                                                                                                                        | 1c = N    |
| [103] | Segments defects from ground penetrating radar data images using Segnet and a changed loss function. <b>Segments ground penetrating radar data images with deep learning.</b>                                                                                            | 1c = N    |
| [63]  | Proposes a deep learning model for extracting multiscale features of water leakages based on mobile laser scanning (MLS) point cloud intensity images. <b>Tunnel image defect segmentation.</b>                                                                          | 1c;2b = Y |
| [49]  | Tunnel image defect segmentation using Mask R-CNN with a path augmentation feature pyramid network and an edge detection branch. <b>Tunnel image defect segmentation.</b>                                                                                                | 1c;2b = Y |
| [183] | Using ROI and K-means clustering pipe recognition is performed on ground-penetrating radar data. <b>Ground-penetrating radar data clustering. Not available under Utwente license.</b>                                                                                   | 1c = N    |
| [184] | Segmentation of transmission electron microscopy data using a decoder-encoder architecture. <b>Segmentation of transmission electron microscopy data.</b>                                                                                                                | 1c = N    |
| [35]  | Segments internal tunnel image for deformations using a UNet with a feature reuse and attention mechanism block. <b>Pipe image segmentation.</b>                                                                                                                         | 1c;2a = Y |
| [185] | Uses a single channel of T1-weighted MR images for segmentation of cortical and subcortical brain areas. <b>Medical image segmentation.</b>                                                                                                                              | 1c = N    |

Continued on next page

| Cite  | Summary                                                                                                                                                                                                                                                                 | Meets     |
|-------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| [186] | Using an encoder-decoder architecture segments pavement defects in orthoframes. <b>Orthoframe pavement defect segmentation.</b>                                                                                                                                         | 1c = N    |
| [36]  | Combines a dense conditional random field with a deep CNN for segmenting pipe internal images. <b>Pipe image segmentation.</b>                                                                                                                                          | 1c;2a = Y |
| [99]  | Segmentation and classification of defects in steam generator tubes magnetic flux leakage images using a shape based feature set and a feed forward neural network. <b>Magnetic flux leakage image segmentation of steam tubes.</b>                                     | 1c = N    |
| [187] | Segmentation of weld defects in radiographic images using FgSegNet. <b>Segmentation in radiographic images.</b>                                                                                                                                                         | 1c = N    |
| [188] | Decompose geomagnetic signals for coupling characteristics of magnetic anomaly signals and different time-frequency scales for finding pipe defects. <b>Decomposes geomagnetic signals for pipeline defect detection.</b>                                               | None = N  |
| [189] | Uses a Mask Region-based Convolutional Neural Network for segmenting tunnel images. <b>Not available under Utwente license.</b>                                                                                                                                         | 1c;2b = N |
| [190] | Uses a CNN with dilated convolution for segmenting pipe defects from images. <b>Pipe image defect segmentation.</b>                                                                                                                                                     | 1c;2a = Y |
| [191] | Uses a modified fuzzy min-max neural network for clustering on benchmark datasets and a magnetic flux leakage pipe inspection dataset. <b>Clustering of magnetic flux leakage data.</b>                                                                                 | 1c = N    |
| [192] | Uses attribute clustering and feature ranking in order to remove redundant features in various medical datasets on DNA microarray classification. <b>DNA microarray classification.</b>                                                                                 | None = N  |
| [193] | Proposes an ontology based information integration framework for building information modeling. <b>Business process modeling for building information modeling.</b>                                                                                                     | None = N  |
| [194] | Proposes a preprocessing algorithm which uses a modified fuzzy min-max neural network for clustering. <b>Almost the same as [191].</b>                                                                                                                                  | 1c = N    |
| [195] | Proposes a method for estimating the corrosion defect depth in pipes based on ultrasonic data using a Bayesian inferential framework. <b>Calibration ultrasonic data for corrosion depth estimation.</b>                                                                | None = N  |
| [196] | Proposes a Multi-Feature Attention Network (Point-MEAN) point cloud segmentation in pipe. <b>Has been removed from SSRN at the request of the author, SSRN, or the rights holder.</b>                                                                                   | 1c;2a = N |
| [50]  | Proposes FlexiCrackNet for crack segmentation on various datasets. Uses EdgeSam's encoder for feature extraction, uses the information interaction gated attention mechanism for multi level feature fusion. <b>Encoder decoder architecture for segmenting cracks.</b> | 1c;2b = Y |

Table A.6: Calibration per paper review.

| Category                | Method                                                                      | Synthetic | Reprojection Error | Other metric | Chessboard | Other target | Compared | Keep | Cited by | FWCI  | Cite  |
|-------------------------|-----------------------------------------------------------------------------|-----------|--------------------|--------------|------------|--------------|----------|------|----------|-------|-------|
| Geometric Models        | N-Sphere refraction model (generalization of [197], [198]) + homography fit | X         | ✓                  | ✓            | ✓          | X            | ✓        | ✓    | 0        | -     | [54]  |
| Distortion Correction   | Transformation matrix (image → world) + Taylor radial correction            | X         | X                  | ✓            | X          | X            | ✓        | ✓    | 15       | 1.17  | [55]  |
| Pattern Projection      | Refraction modeling + sinusoidal projection + phase shifting/unwrapping     | X         | ✓                  | X            | X          | ✓            | X        | X    | 8        | 0.52  | [88]  |
| Spherical Transforms    | Ellipse extraction + spherical mapping + radial/tangential correction       | X         | X                  | ✓            | ✓          | X            | X        | X    | 0        | -     | [112] |
|                         | 3D rotation matrix + spherical remap + 2D projection                        | X         | X                  | X            | X          | X            | X        | X    | 4        | 0.27  | [113] |
|                         | Hough transform + spherical projection + bilinear interpolation             | X         | X                  | X            | X          | X            | X        | X    | 3        | 1.22  | [115] |
| Polynomial models       | Polynomial projection mapping 3D rays → image points                        | ✓         | ✓                  | ✓            | X          | ✓            | ✓        | ✓    | 813      | 9.74  | [56]  |
|                         | Homography estimation + nonlinear optimization                              | ✓         | X                  | ✓            | X          | ✓            | X        | ✓    | 13474    | 28.37 | [24]  |
| Laser-plane Calibration | Zhang's method [24]                                                         | X         | X                  | ✓            | ✓          | X            | X        | ✓    | 0        | -     | [14]  |
|                         | Camera intrinsics [71] + laser [75]                                         | X         | ✓                  | ✓            | ✓          | X            | X        | ✓    | 3        | 0.88  | [17]  |
|                         | Zhang's method [24] + least squares                                         | ✓         | X                  | X            | ✓          | X            | X        | X    | 0        | -     | [13]  |
|                         | Intrinsics [24] + extrinsics [73, 199]                                      | X         | X                  | X            | X          | ✓            | X        | X    | 9        | 0.35  | [15]  |
|                         | Homography + 3D calibration [200]                                           | X         | ✓                  | ✓            | X          | ✓            | X        | ✓    | 0        | -     | [16]  |
|                         | Adjusted Zhang's method [24, 74]                                            | X         | X                  | X            | X          | ✓            | X        | X    | 0        | -     | [58]  |
|                         | Zhang's method [24] + optimization (circular ring gauge)                    | X         | X                  | ✓            | X          | ✓            | X        | ✓    | 26       | 1.69  | [68]  |

Table A.7: Reconstruction per paper review.

| Category             | Method                                                                                | Qualitative | Synthetic | Partial geometry | Known geometry | Keep | Cited by | FWCI | Cite  |
|----------------------|---------------------------------------------------------------------------------------|-------------|-----------|------------------|----------------|------|----------|------|-------|
| Laser profilometry   | Line extraction + triangulation + stacking + mesh                                     | ✓           | X         | X                | X              | ✓    | 8        | 0.69 | [12]  |
|                      | Line extraction + triangulation + stacking                                            | ✓           | X         | ✓                | ✓              | ✓    | 0        | -    | [14]  |
|                      | Line extraction + triangulation + stacking                                            | ✓           | ✓         | X                | X              | ✓    | 0        | -    | [13]  |
|                      | Line extraction + triangulation + stacking                                            | ✓           | X         | ✓                | X              | ✓    | 0        | -    | [16]  |
|                      | Stereo line extraction + circle fitting + triangulation + ICP                         | ✓           | X         | ✓                | X              | ✓    | 59       | 3.68 | [18]  |
|                      | Line extraction + stereo calibration + triangulation + radius map, not reconstruction | X           | X         | ✓                | ✓              | X    | 25       | 1.69 | [68]  |
| Ambient Illumination | Cylindrical unwrapping + optical flow-based stitching + rewrap                        | ✓           | X         | X                | X              | ✓    | 9        | 1.12 | [4]   |
|                      | Line extraction with transformer + triangulation + ICP                                | ✓           | X         | ✓                | ✓              | ✓    | 0        | -    | [58]  |
|                      | Cylindrical unwrapping + binarization + heuristic classification, not reconstruction  | X           | X         | X                | X              | X    | 15       | 1.51 | [105] |
| Laser range sensing  | Triangulation + stacking                                                              | ✓           | X         | ✓                | X              | ✓    | 9        | 0.35 | [15]  |

Continued on next page



|                         |                                                                                                            |   |   |   |   |   |    |      |      |
|-------------------------|------------------------------------------------------------------------------------------------------------|---|---|---|---|---|----|------|------|
| Laser range sensing     | Distance/Gyroscope + coordinate conversion + mesh                                                          | ✓ | ✗ | ✗ | ✗ | ✓ | 1  | 0.27 | [20] |
|                         | Outlier removal + slice alignment + stacking                                                               | ✓ | ✗ | ✓ | ✗ | ✓ | 15 | 1.51 | [21] |
| Pattern projection      | Line extraction + triangulation + stacking + mesh                                                          | ✓ | ✗ | ✓ | ✗ | ✓ | 15 | 0.94 | [28] |
| Multisensor Fusion SLAM | Optical flow (ambient light) + state (IMU) + point cloud (LiDAR)                                           | ✓ | ✗ | ✗ | ✗ | ✓ | 0  | –    | [57] |
|                         | Optical flow (ambient light) + state (IMU) + point cloud (LiDAR & laser profile detection + triangulation) | ✓ | ✗ | ✓ | ✓ | ✓ | 3  | 0.88 | [17] |

Table A.8: Segmentation per paper review.

| Category     | Method                                                       | Recall | Precision | Accuracy | F1 | IoU | Dice | Pixel Accuracy | Speed | Compared > 1 | Ablation | Keep | Cited by | FWCI  | Cite  |
|--------------|--------------------------------------------------------------|--------|-----------|----------|----|-----|------|----------------|-------|--------------|----------|------|----------|-------|-------|
| Point clouds | BCSF + DBSCAN/RG                                             | ✗      | ✗         | ✗        | ✓  | ✓   | ✗    | ✗              | ✗     | ✓            | ✗        | ✓    | 1        | –     | [22]  |
|              | DBSCAN + RG                                                  | ✗      | ✓         | ✗        | ✗  | ✗   | ✗    | ✗              | ✓     | ✓            | ✗        | ✓    | 15       | 1.51  | [21]  |
|              | Adjusted PointNet++                                          | ✓      | ✓         | ✓        | ✓  | ✓   | ✗    | ✗              | ✓     | ✓            | ✓        | ✓    | 24       | 5.70  | [11]  |
|              | Adjusted UNet + neighborhood                                 | ✓      | ✓         | ✓        | ✓  | ✓   | ✗    | ✗              | ✓     | ✓            | ✓        | ✓    | 0        | –     | [60]  |
|              | Euclidean clustering + kd-tree up sampling                   | ✓      | ✓         | ✗        | ✓  | ✓   | ✗    | ✗              | ✗     | ✓            | ✗        | ✓    | 0        | –     | [64]  |
|              | Graph embedding CNN                                          | ✗      | ✗         | ✗        | ✗  | ✓   | ✗    | ✗              | ✓     | ✓            | ✓        | ✓    | 0        | –     | [61]  |
|              | Adjusted UNet                                                | ✗      | ✗         | ✗        | ✗  | ✓   | ✗    | ✗              | ✗     | ✓            | ✓        | ✓    | 28       | 3.25  | [62]  |
|              | Mask R-CNN + Cascade R-CNN                                   | ✗      | ✓         | ✗        | ✗  | ✗   | ✗    | ✗              | ✓     | ✓            | ✗        | ✓    | 48       | 3.49  | [63]  |
|              | RANSAC + circular fit + thresholding                         | ✗      | ✗         | ✓        | ✗  | ✗   | ✗    | ✗              | ✗     | ✗            | ✗        | ✗    | 5        | 2.37  | [106] |
|              | Transformer + self attention + classification                | ✓      | ✓         | ✗        | ✓  | ✗   | ✗    | ✗              | ✗     | ✓            | ✓        | ✓    | 76       | 5.20  | [23]  |
| Images       | Graph CNN                                                    | ✓      | ✓         | ✓        | ✓  | ✓   | ✗    | ✗              | ✗     | ✓            | ✗        | ✓    | 21       | 2.13  | [59]  |
|              | Semi-bilateral efficient SAN                                 | ✗      | ✗         | ✗        | ✗  | ✓   | ✗    | ✗              | ✓     | ✓            | ✓        | ✓    | 1        | –     | [29]  |
|              | Adjusted UNet (KAN)                                          | ✓      | ✓         | ✗        | ✓  | ✓   | ✗    | ✗              | ✗     | ✓            | ✓        | ✓    | 0        | –     | [30]  |
|              | Adjusted DeepLabV3+ (MobileNetV2 + strip pooling)            | ✗      | ✗         | ✗        | ✗  | ✓   | ✗    | ✓              | ✓     | ✓            | ✗        | ✓    | 0        | –     | [27]  |
|              | Adjusted UNet (ResNet50 + Transformer)                       | ✓      | ✗         | ✓        | ✓  | ✓   | ✗    | ✓              | ✗     | ✓            | ✗        | ✓    | 14       | 2.69  | [31]  |
|              | Adjusted YOLOv8                                              | ✓      | ✓         | ✗        | ✗  | ✓   | ✗    | ✗              | ✗     | ✗            | ✓        | ✗    | 3        | 2.37  | [170] |
|              | Adjusted MobileNetV2                                         | ✓      | ✓         | ✗        | ✓  | ✓   | ✗    | ✗              | ✓     | ✓            | ✓        | ✓    | 5        | 0.81  | [32]  |
|              | StyleGAN3 + adjusted SparseInst                              | ✗      | ✓         | ✗        | ✗  | ✓   | ✗    | ✗              | ✓     | ✓            | ✗        | ✓    | 4        | 0.47  | [33]  |
|              | Thresholding, edge detection, RG, clustering                 | ✗      | ✗         | ✗        | ✗  | ✗   | ✗    | ✗              | ✗     | ✗            | ✗        | ✗    | 1        | 1.32  | [180] |
|              | Attention-based CNN + GAN + Yolact                           | ✗      | ✓         | ✗        | ✗  | ✓   | ✗    | ✗              | ✓     | ✓            | ✗        | ✓    | 48       | 3.26  | [34]  |
|              | Adjusted UNet (Attention)                                    | ✓      | ✓         | ✓        | ✓  | ✓   | ✗    | ✗              | ✗     | ✓            | ✗        | ✓    | 99       | 3.35  | [35]  |
|              | Dilated multiscale CNN with CRF                              | ✗      | ✗         | ✗        | ✗  | ✓   | ✗    | ✓              | ✓     | ✓            | ✗        | ✓    | 143      | 6.91  | [36]  |
|              | Dilated multiscale CNN                                       | ✗      | ✗         | ✗        | ✗  | ✓   | ✗    | ✓              | ✓     | ✗            | ✗        | ✗    | 14       | 4.24  | [190] |
|              | Adjusted YOLOv11                                             | ✓      | ✓         | ✗        | ✗  | ✓   | ✗    | ✗              | ✗     | ✗            | ✓        | ✓    | 0        | –     | [37]  |
|              | SAM + adjusted YOLOv5                                        | ✓      | ✓         | ✗        | ✓  | ✗   | ✗    | ✗              | ✓     | ✓            | ✗        | ✓    | 6        | 4.55  | [38]  |
|              | Adjusted DeepLabV3+                                          | ✗      | ✗         | ✓        | ✗  | ✓   | ✗    | ✓              | ✗     | ✓            | ✓        | ✓    | 1        | –     | [39]  |
|              | Adjusted UNet (residual + edge refinement)                   | ✗      | ✗         | ✓        | ✗  | ✓   | ✓    | ✓              | ✗     | ✗            | ✗        | ✗    | 2        | 2.19  | [97]  |
|              | Adjusted YOLOv10-Seg                                         | ✗      | ✓         | ✗        | ✓  | ✓   | ✗    | ✗              | ✓     | ✓            | ✓        | ✓    | 0        | –     | [40]  |
|              | Adjusted UNet (extra tree + Otsu binarization)               | ✗      | ✗         | ✓        | ✗  | ✓   | ✓    | ✓              | ✓     | ✓            | ✓        | ✓    | 4        | 0.95  | [41]  |
|              | Adjusted ViT (conv. adapters + pyramid decoder)              | ✓      | ✓         | ✓        | ✓  | ✓   | ✗    | ✗              | ✓     | ✓            | ✓        | ✓    | 28       | 5.88  | [42]  |
|              | CNN + Transformer with pyramid fusion                        | ✗      | ✗         | ✓        | ✗  | ✓   | ✗    | ✓              | ✗     | ✓            | ✓        | ✓    | 3        | 0.64  | [43]  |
|              | SAM + adjusted YOLOv8 + UNet                                 | ✓      | ✓         | ✗        | ✗  | ✗   | ✗    | ✗              | ✗     | ✓            | ✗        | ✓    | 34       | 7.36  | [44]  |
|              | Adjusted UNet (pyramid attention + global upsampling)        | ✗      | ✗         | ✓        | ✗  | ✓   | ✗    | ✓              | ✓     | ✓            | ✓        | ✓    | 3        | 0.73  | [45]  |
|              | Adjusted YOLOv7 + DeepLabV3+                                 | ✓      | ✓         | ✓        | ✗  | ✓   | ✗    | ✓              | ✓     | ✓            | ✗        | ✓    | 4        | 0.84  | [46]  |
|              | Adjusted UNet (ResNet50 + RCCA + ASPP)                       | ✗      | ✗         | ✓        | ✗  | ✓   | ✗    | ✓              | ✗     | ✓            | ✓        | ✓    | 40       | 3.73  | [47]  |
|              | Adjusted UNet/UNet++                                         | ✓      | ✓         | ✗        | ✓  | ✓   | ✗    | ✗              | ✗     | ✓            | ✗        | ✓    | 36       | 4.12  | [48]  |
|              | Adjusted FCN                                                 | ✗      | ✗         | ✓        | ✗  | ✓   | ✗    | ✓              | ✗     | ✗            | ✗        | ✗    | 0        | –     | [178] |
|              | MobileNetV3 + adjusted UNet                                  | ✗      | ✗         | ✓        | ✗  | ✗   | ✗    | ✗              | ✗     | ✗            | ✗        | ✗    | 3        | 4.22  | [177] |
|              | Adjusted Mask R-CNN                                          | ✓      | ✓         | ✗        | ✗  | ✗   | ✗    | ✗              | ✗     | ✓            | ✓        | ✓    | 209      | 11.90 | [49]  |
|              | SAM + adjusted UNet                                          | ✗      | ✗         | ✗        | ✓  | ✓   | ✓    | ✗              | ✓     | ✓            | ✓        | ✓    | 0        | –     | [50]  |
|              | 2D CNN with transfer learning, CNN-LSTM, Cross layer pooling | ✓      | ✓         | ✓        | ✗  | ✗   | ✗    | ✗              | ✗     | ✓            | ✗        | ✓    | 13       | 0.99  | [19]  |