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Classification of Welds Using Neural Networks trained on Synthetic Data

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Abstract

The advancement of digital inspection systems has enabled data-driven visual testing of welds, allowing systematic, repeatable, and quantitative assessment. These improvements can be implemented in the fatigue assessment of structures subjected to cyclic loading, particularly where local weld imperfections govern overall strength. With resolutions significantly finer than traditional analogue methods, imperfections can be identified more systematically and reliably than with manual visual testing. However, digital representations of welds introduce the challenge of reliably identifying and classifying weld regions and imperfections, a task that is straightforward for a human inspector but non-trivial to perform numerically. Neural networks are well-established for segmentation tasks and have recently been applied to weld inspection, where their compatibility with digital measurement data makes them suitable for classifying imperfections. When using real-world training data, the network requires ground truth labels, which are labour-intensive to produce and may introduce subjectivity. An alternative is synthetic data with deterministic ground truth, offering access to large, controlled datasets. However, the question remains how well a network trained on synthetic data generalize to real-world data. This work presents an approach for classification of weld surfaces using synthetic training data. The proposed method employs a U-net-based neural network architecture to classify unwelded base material, the weld bead, and the transition zone. The training data consists of synthetic butt and fillet welds generated with varying global and local geometric parameters. A stochastic data generation framework is proposed that uses an Ornstein–Uhlenbeck process to emulate natural variability in welds and measurement systems. The statistical properties of the generated welds are based on previously reported measurements, while parameter

distributions are uniformly sampled from ISO 5817 quality levels. The trained model is evaluated qualitatively on scans of real welds, demonstrating that models trained on synthetic data can identify and classify weld regions.

Keywords

Digital visual testing, Synthetic weld geometry, Non-destructive testing (NDT), Neural networks, Weld surface segmentation

1. Introduction

Visual testing of welds can be considered the first non-destructive testing (NDT) method and can to this day still be considered the most common. Like other NDT methods visual testing has drawbacks, specifically the resolution not being fine enough for modern demands on weld geometry. Demands which are found in many industries which concern with designing against cyclical fatigue loading. The connection between fatigue performance of welds and weld quality, as standardized by international organizations, has been studied in the past decades [1][2][3], cementing the connection between fatigue performance, NDT and visual testing. More recent studies have shown that local variations in weld geometry, such as weld toe radius and angle, influence the local stress concentrations and by extension the fatigue strength of welded joints [4][5]. Studies have also been made trying to connect the variation in local weld geometry to fatigue assessment [6], showing that there are still novel methods to predict the fatigue life of welded components.

Hammersberg and Olsson [7] showed that with increasing performance of welding processes comes increasing demands on inspection systems. The comprehensive studies carried out by Hammersberg and Olsson and later on by Stenberg et al [8] were based on round robin weld quality measurements in different welding workshops using at date common analogue tools for this purpose. The studies showed that the measurement tools contributed to almost 60% variation in the measurement, even for as simple local weld dimensions as the throat thickness. Figure 1 illustrates some of these results reported by Hammersberg and Olsson.

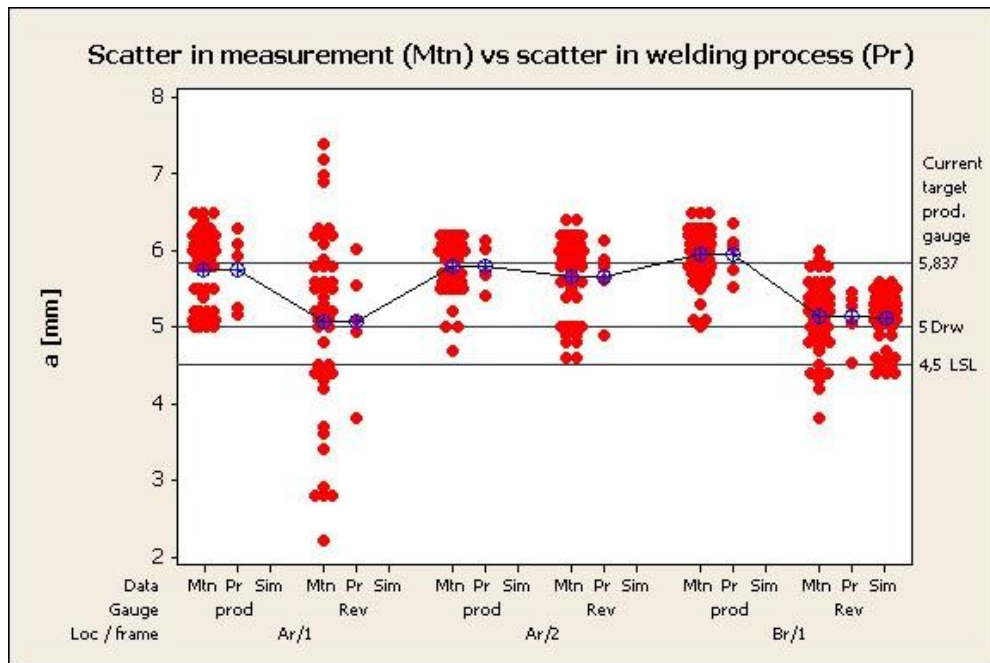


Figure 1: Scatter of analogue measurements of throat thickness measured with two different gauges [7].

Analogue weld inspection and measurement tools often feature manual scales with a resolution of a tenth of a millimetre. This makes it impossible to assess quality at that level of precision when using standard conventions like the Gage Maker's Rule or the 10:1 Rule [9], which require the gauge to be at least ten times more accurate than the measurement. Analogue scales are moreover associated with lack of automated data recording, slow process and proneness to human error. Which motivates the continuous development of more advanced digital inspection systems and data recording. One of the recently frequently used systems for digital visual inspection (D-VT), Winteria®, is illustrated in Figure 2, below.

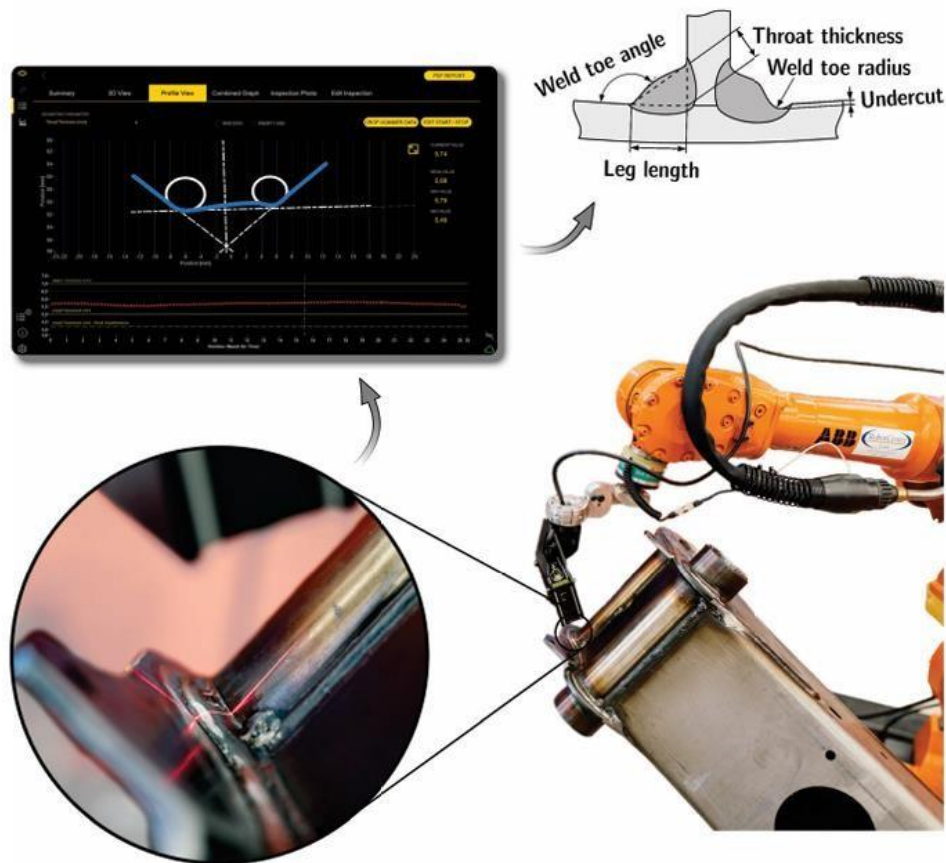


Figure 2: Schematic representation of the Winteria® D-VT system.

A testament of these new inspection systems can be seen in the recent studies which have been enabled by the advance of digital measuring systems which can now be accredited for giving rise for the field of D-VT [10] and data-driven evaluation of welds. Ideas of data-driven, specifically machine learning and artificial intelligence, quality assurance in manufacturing processes, like welding, have been around for decades [11] but have, in recent years rapidly been put into practice through the industry 4.0 paradigm [12]. With measurement systems producing information-rich data machine learning has been used to predict weld bead geometry [13], classify weld defects in radiographical images [14], and determining stress concentration factors in welded joints [15]. With the emergence of high-resolution laser scanning systems and D-VT methods, weld inspection data can increasingly be represented as structured spatial data suitable for computer vision and machine learning applications. In particular, convolutional neural networks (CNNs) have shown strong performance in image segmentation tasks due to their ability to extract hierarchical spatial features while preserving local geometric information. This creates the possibility of automating parts of the weld inspection process by directly identifying and segmenting weld regions directly from scanned geometric data.

With traditional visual testing requiring a trained inspector using analogue gauges and weld measuring equipment [16] it can be considered an expensive and potentially inaccurate NDT method. Inaccurate in the sense that analogue gauges give a binary pass or fail and weld measurement equipment requires

the inspector's subjective opinion of where to measure. Still, it is a method asked for in industry standards for weld quality.

General digital measuring equipment is an established technology and consists of two parts. First, the hardware which digitizes what is to be measured and secondly the post-processing or rather the actual measuring. For digitizing welds some examples of hardware are stripe light projectors [11], fringe light projectors and laser line scanners (LLS) [17]. The proposed work concerns laser line scanners which produce 2D weld profiles which can be stacked to produce a 3D weld representation or weld scan, a process visualized in Figure 3. With a 3D representation of the weld in a Cartesian coordinate system, geometrical features such as weld-toe radius and can be derived and or measured. However, this is not a trivial task as a recent round robin study showed with the scatter in the results [18]. To numerically determine these features the weld seam often needs to be identified in the scan and act as an initial value or a boundary in the numerical algorithm. To remove ambiguity of what is considered the weld seam as well as to create a repeatable and traceable determination of the location of the weld seam, the scan data can be used to train a neural network.

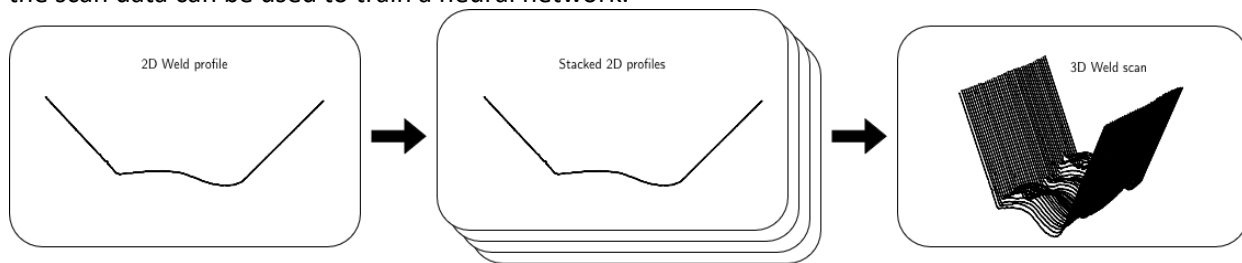


Figure 3: Schematic representation of the creation of the weld scan.

In this work, laser-scanned weld profiles are represented as image-like data structures with each scan profile corresponding to a spatial measurement of the weld geometry. A CNN based on the U-net architecture is trained to perform semantic segmentation of weld regions from scanned data. Due to the limited availability of annotated weld-scan datasets, synthetic weld geometries are generated to create a controllable and scalable training dataset. The objective of the work is to investigate the applicability of deep-learning based image segmentation for automated analysis of laser-scanned weld geometries.

2. Machine learning approaches for D-VT

2.1 Image segmentation

A laser line scanner produces ordered data with a defined height and width. Individual scan profiles, corresponding to cross-sections of the weld, form the height dimension, while the scan progression along the weld forms the width dimension. The resulting data can therefore be represented as a matrix of fixed height and width, where each element contains the coordinates measured by the scanner forming a channel dimension. This structure is analogous to a digital image, consisting of spatial dimensions and one or more channels.

Image segmentation was an early application of machine learning and is commonly found in research concerning medical image processing. With weld scanning data being a 3D representation a natural application is using neural networks intended for 3D point cloud data as studied by Baumgartner et al

[17] with their work using the pointnet++ to find the weld seam in a scanned representation of a fillet weld.

With the data from the LLS sharing similar features with a 2D image more classical image segmentation algorithms could be used to find a weld seam in the scan. One of these could be the U-net proposed by Ronneberger et al [19] in 2015. This CNN for biomedical image segmentation relied heavily on data augmentation to work around not having an extensive annotated dataset, something that is a common problem across all machine learning applications.

2.2 The use of synthetic data

Training neural networks generally requires large, annotated datasets to train. In the context of weld scans, the challenges in obtaining this training data are not unique. While modern LLS can produce large amounts of geometric information at little effort, annotating the data often requires expert knowledge and considerable manual effort. One approach to these challenges is the use of synthetic data. By generating digital weld scans, large datasets can automatically be created with annotations. This provides full control over weld geometry, weld defects, scanner settings and noise. A major benefit is also that the annotations can be mathematically motivated.

However, synthetic data also comes with challenges. The generated dataset will always be an approximation and simplification of the stochastic and complex nature of real welds, which seldom conform to idealized geometrical descriptions. The performance of a neural network trained on synthetic data will be reliant on the discrepancy between simulated data and real-world measurements. The use of approximate synthetic data therefore raises the question of the extent of which a network trained exclusively on synthetic data will be able to generalize real-world data. A question this work aims to investigate.

3. Method

The method consisted of two main tracks, the network architecture and the data generation. The creation of the U-net relied heavily on prior work and some heuristics to better suit the architecture to the dimension of the data. The synthetic data generation took footing in the format of the real data and was then tweaked to more reliably represent the features of the real data with the inclusion of some random elements to provide variation in the dataset. The resulting model was qualitatively evaluated on scans of real butt and fillet-welds produced by two different scanners.

3.1 Data, format & generation

3.1.1 Data format

The synthetic training data used in this work was generated to mimic raw measurements acquired using a Micro-Epsilon LLT30x0-50 laser scanner [20]. The scanner acquires a sequence of two-dimensional weld profiles, each consisting of up to 2048 measured points across the weld cross-section. In the image representation used throughout this work, the profile direction is defined as the height dimension, while the scan progression along the weld defines the width dimension. The resulting point cloud data can therefore be interpreted as an ordered matrix of profiles. For each profile, the measured lateral coordinates and profile heights are stored separately, resulting in alternating rows containing the x- and y-coordinates respectively, forming the profile shown in Figure 4a.

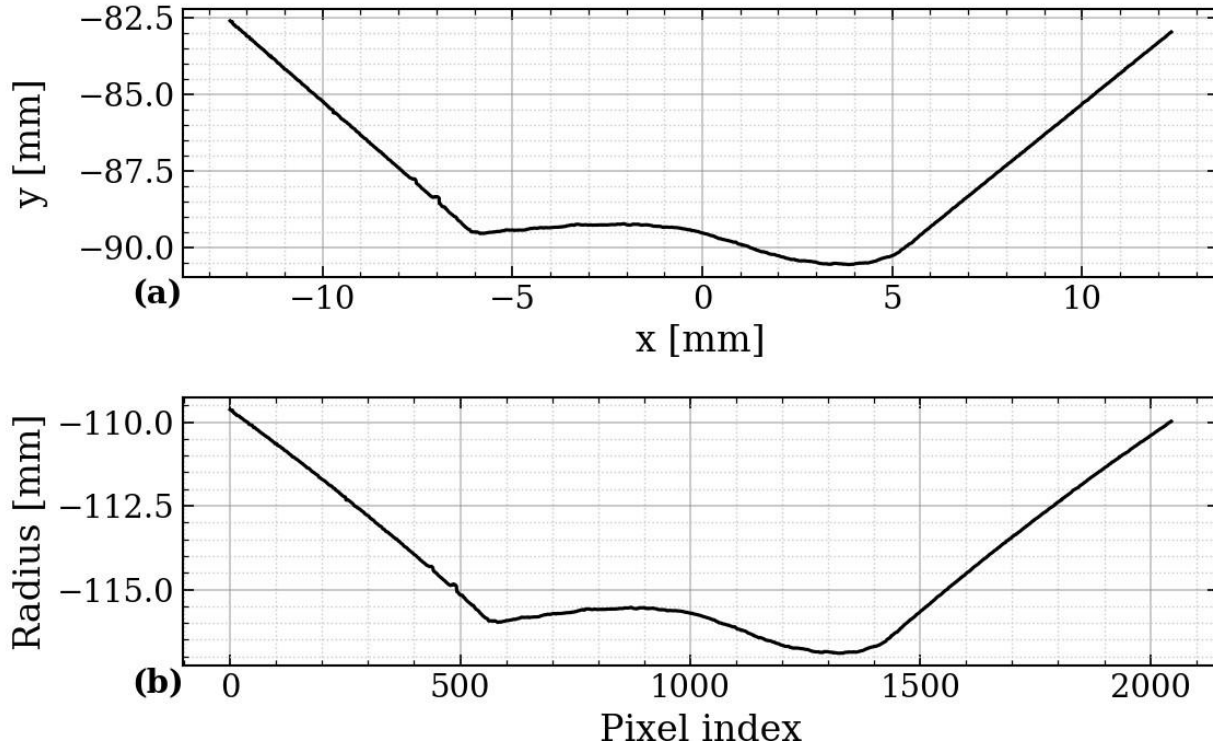


Figure 4: Example weld profile. Raw Cartesian coordinates in (a) and the radial coordinates of the same profile in (b).

To reduce the sensitivity of the neural network to scanner inclination and weld rotation, the Cartesian coordinates are transformed into polar coordinates. The angular difference between samples was considered constant and the angular coordinate was therefore replaced with pixel index before being used as network input. This representation, visualized in Figure 4 (b), is defined, for the scanner at hand, as

$$r = \sqrt{x^2 + y^2} \quad (1)$$

And

$$\theta = \arctan\left(\frac{x}{y}\right) \quad (2)$$

where r represents the radial distance and θ the angular position relative to the scanner coordinate system. As the scanner beams radiate in constant angular steps from a common focal point θ is constant for the dataset.

3.1.2 Mathematical description of weld profile

The generation of a 2D weld profile is based on idealized weld profile geometry in the IIW Best Practice Guideline for Digital Visual Testing (D-VT)-Part 1 document [10], and the seven variables that describe the weld profile geometry. These variables are toe radius, flank angle (supplementary angle

to the weld toe angle), weld bead width, plate angle, undercut depth, undercut opening angle and plate misalignment, as seen in Figure 5. The two halves of the weld profile are generated independently to later be joined into a continuous curve. For each half, the local profile is constructed from a sequence of analytical curve segments. First, the weld bead is described by a hyperbolic cosine function, which defines the convex bead shape from the weld centreline towards the weld toe. Secondly, the transition between the weld bead and the non-welded base material is defined as a circular arc with a prescribed radius, representing the weld toe radius. The position of the circular transition arc is determined by the bead width, flank angle, plate angle, and weld toe radius.

If the generated weld profile is to contain an undercut the circular weld toe arc is extended by an additional angle parameter. From the end of this extension a tangent segment is constructed towards the base plate. Undercut geometry is then introduced by applying an offset normal to the plate surface before determining the intersection between the tangent segment and the plate. The extended arc angle and plate offset are set and represented by the opening angle and depth of the intended undercut. The transition area is in this case determined by the intersection of the extended arc and the base plate.

The resulting side profile is therefore defined as a piecewise analytical function consisting of the key points/boundaries which describe the weld bead, the weld toe radius, base plate and optionally the undercut region. This construction allows the left and right sides of the weld to be generated independently, enabling asymmetric weld geometries.

A major benefit of working with synthetic data is the data labelling aspect. Instead of tasking a team of people with manually labelling real-world data the use of synthetic data can anchor the labels in the training data in a mathematical definition. Key points defining the weld profile the weld transition zones were defined as the points from where the undercut arc starts and the weld toe radius arc ends as seen in Figure 5. This definition stands even if the undercut is not present as the start of the undercut arc moves towards the start of the weld toe radius.

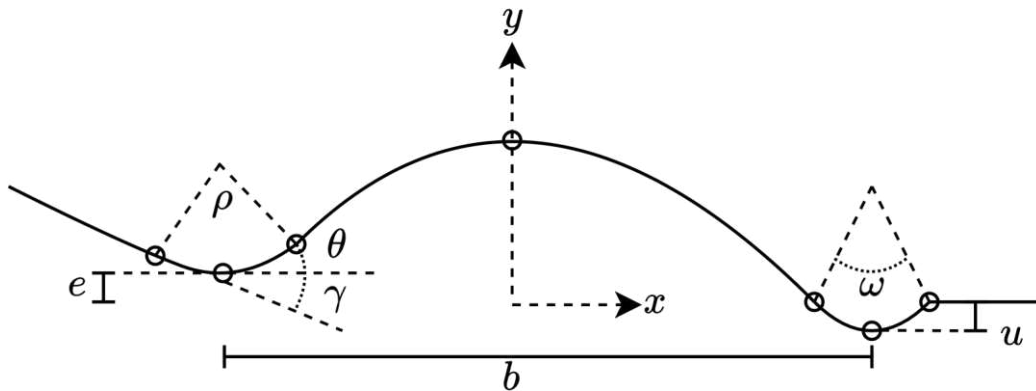


Figure 5: Parameter defined weld profile where e , ρ , θ , γ , b , ω and u are the eccentricity, weld toe radius, flank angle, plate angle, weld bead width, undercut opening angle and undercut depth respectively.

3.1.3 Parameter choice

Random sampling of the geometrical parameters was used to increase variability in the training data. This sampling was, to keep a connection to real-life welds, taken from a set connected to literature. A

framework based on both previous work and current industry standards such as ISO 5817 [21] and the VOLVO STD 181-0004 standard [22] was created to automatically generate a synthetic weld.

The data generation process consists of two parts. The first is generating a manifest describing the weld to be generated. The second part is reading the manifest and generating the synthetic scan accordingly. The generation of the manifest, visualized in Figure 6, begins with randomizing three key parameters: weld size, quality level and joint type. The quality levels are a direct reference to ISO 5817 [21] and the joint type is either a butt joint or a fillet joint. These three key parameters are combined with a random six-figure number, which acts as the seed in the generator, to form the scan ID. The scan ID is then what sets the ranges from which the geometry parameters are drawn uniformly. The scanner settings were also drawn uniformly with ranges set so that the top of the weld bead could not end up outside of the measuring range of the simulated scanner. The stochastic parameters used in the remainder of the process were set based on previous studies measuring the variability in weld geometry [23][24][25]. The values used can be seen in Table 1 where the parameters with an asterisk were considered design parameters, such as plate angle which was either 0 or 90 degrees.

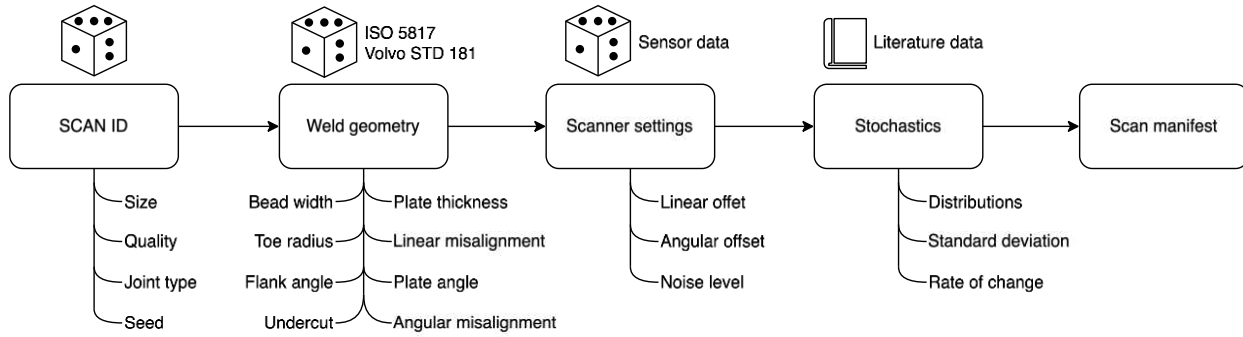


Figure 6: A schematic figure showing the process used in the choice of parameters.

3.1.4 Generating a full scan using Ornstein-Uhlenbeck

To complete a full synthetic weld scan, an Ornstein-Uhlenbeck (OU) mean-reverting process was used to generate the discrete signal along the weld signal parameters. This discrete signal is designed to mimic a scan which samples at 0.2 mm intervals, which has been proposed as suitable sampling distance for fatigue loaded welds in the Q-IN-MAN project [26][27]. This mean reverting process generates a random value based on the previous value of the signal, the mean, standard deviation and noise distribution. The signal $y[k]$ can then be described as

$$y[k] = \theta y[k - 1] + \sigma v[k] + \mu[k] \quad (3)$$

where θ is the rate of mean reverting, which controls how fast the signal returns to a mean represented by a linear trend $\mu[k]$ which is derived, together with the global standard deviation σ , from the start and end values of the signal. $v[k]$ is noise following any given distribution.

The rate of change, θ was determined by qualitatively comparing an arbitrary signal generated with a set seed and different values of θ with a measured signal as in Figure 7 where a generated signal for the weld toe radius was compared with a measured signal of a real-world ditto [27].

To increase similarity to real-world welds a signal was generated for each of the geometrical parameters used in generating the welds as to capture how some parameters change more rapidly than others [27]. Each parameter was assigned its respective θ to reflect the rate of change along the weld.

The OU-process was implemented by drawing a linear trend between a start and end value acting as the mean of which the noise, $v[k]$ fluctuates around. These start and end values were sampled using a Gaussian distribution with a mean equivalent to the value recorded in the manifest and a standard deviation which is presented in Table 1. The exceptions were the so-called design parameters. Sampling the start and end values for the design parameters was done using a standard deviation of two degrees for the plate angle, one degree for the rotational offset as well as one and two mm for the lateral offset and transverse offset respectively. The full synthetic scan was created using the OU-signals of each parameter, as described in sections 3.1.2 and 3.1.4, along the weld to produce the individual weld profiles that make up the full weld length.

The distribution of the geometrical parameters used in the data can be seen in Figure 8 and an example of a synthetic weld profile from a full synthetic scan can be seen in Figure 9.

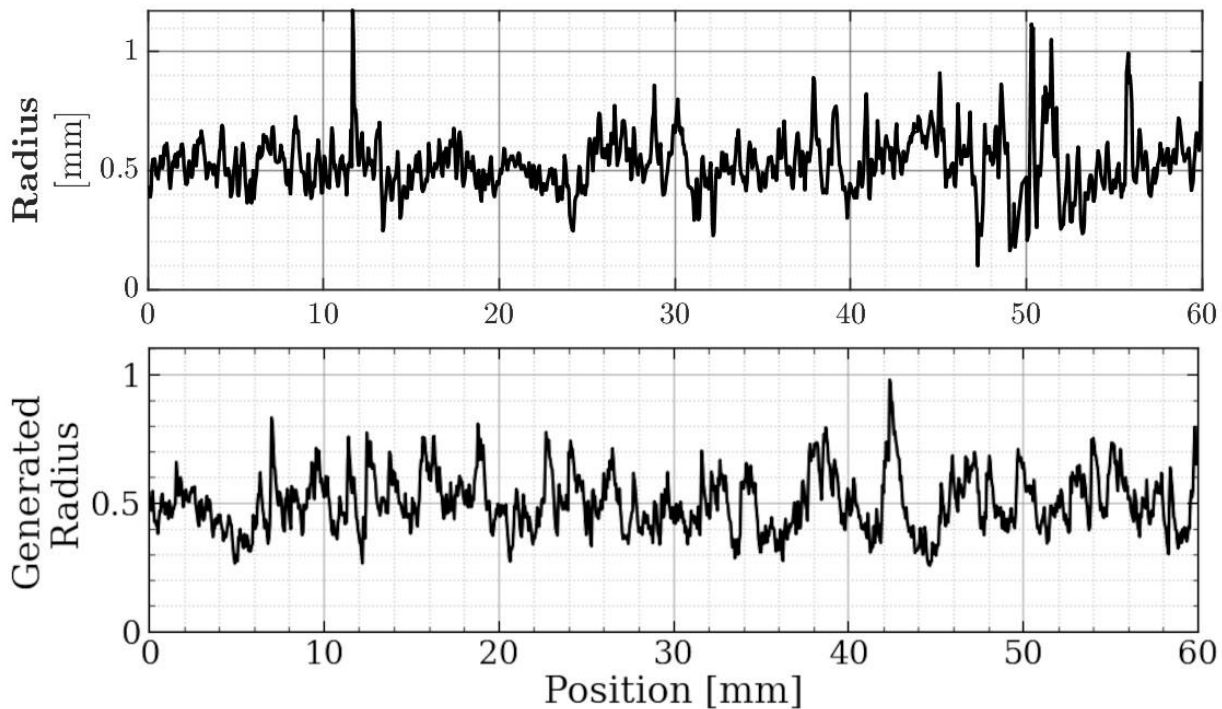


Figure 7: Measured weld toe radius along a weld seam (top) and a corresponding synthetic signal generated using an OU-process with $\theta = 0.1$ (bottom). The figure illustrates how the selected process parameters produce geometric variations resembling those observed in real weld measurements.

Parameter	Standard deviation	OU-distribution	θ
Toe radius	0.379 [mm]	log-normal	0.1
Bead width	0.324 [mm]	normal	0.01
Flank angle	6.00 [deg]	normal	0.01
Plate angle*	2.00 [deg]	normal	0.001
Undercut opening angle	1.50 [deg]	normal	0.01
Undercut depth	0.032 [mm]	log-normal	0.01
Eccentricity	0.10 [mm]	normal	0.001
Transverse offset*	2.00 [mm]	normal	0.01
Lateral offset*	1.00 [mm]	normal	0.01
Rotational offset*	1.00 [deg]	normal	0.01

Table 1: Stochastic values used in the data generation.

To simulate measurement uncertainty in the scanner in each profile, noise was added along the laser beam direction rather than to each Cartesian coordinate. This was done by generating two normally distributed noise components: one primary with standard deviation σ_{main} and one secondary with standard deviation σ_{sub} . The standard deviations were derived from the, in the manifest, generated noise level parameter. The resulting measurement error was obtained by subtracting the secondary component from the primary whilst keeping the sign of the primary. This yields a noise distribution concentrated around zero while still allowing occasional larger deviations. The noise was then projected onto the Cartesian coordinate system using the local beam angle. This noise model was created with a heuristic approach rather than trying to replicate the specific noise produced by a certain laser scanner.

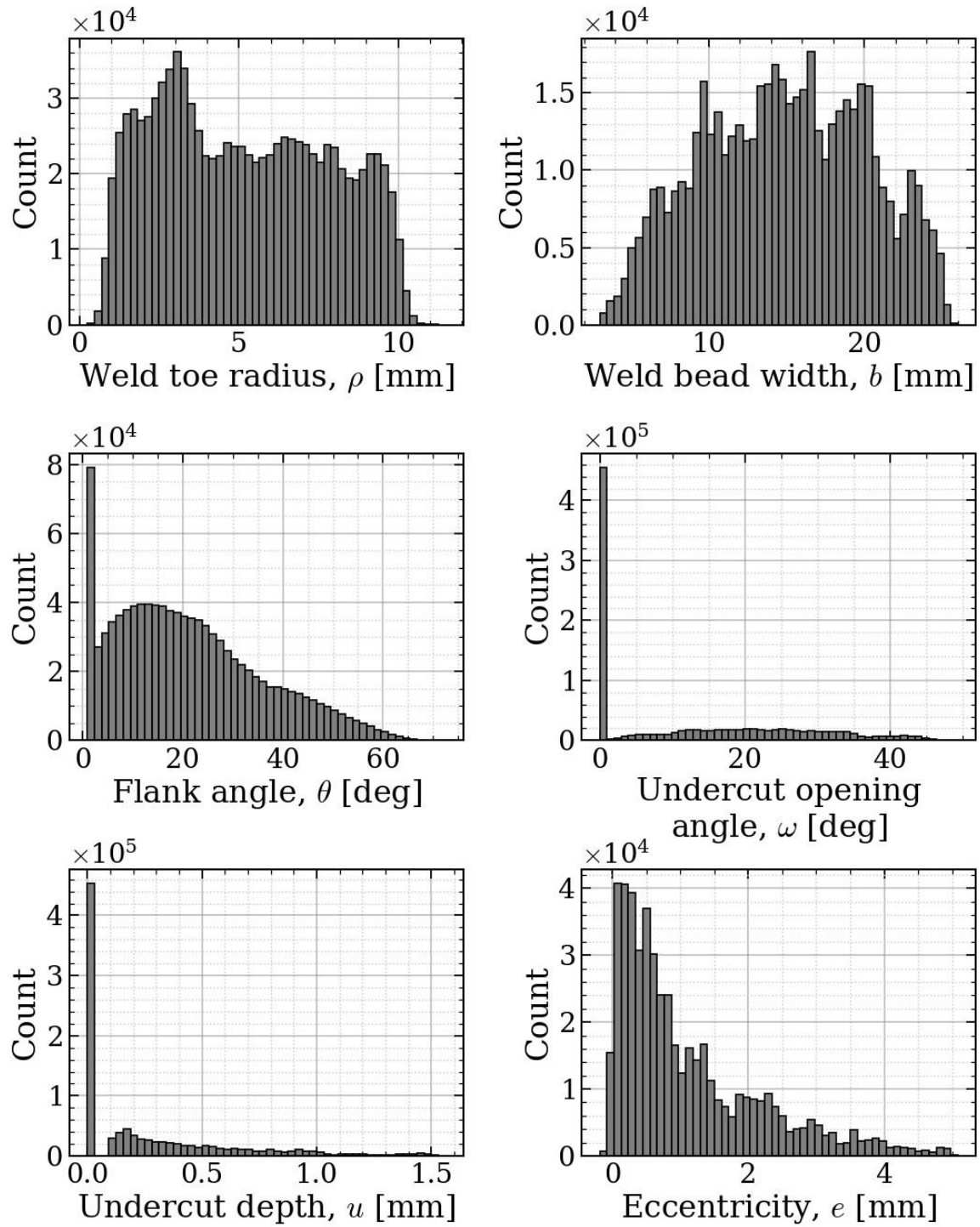


Figure 8: Histogram of the parameters used in the training data.

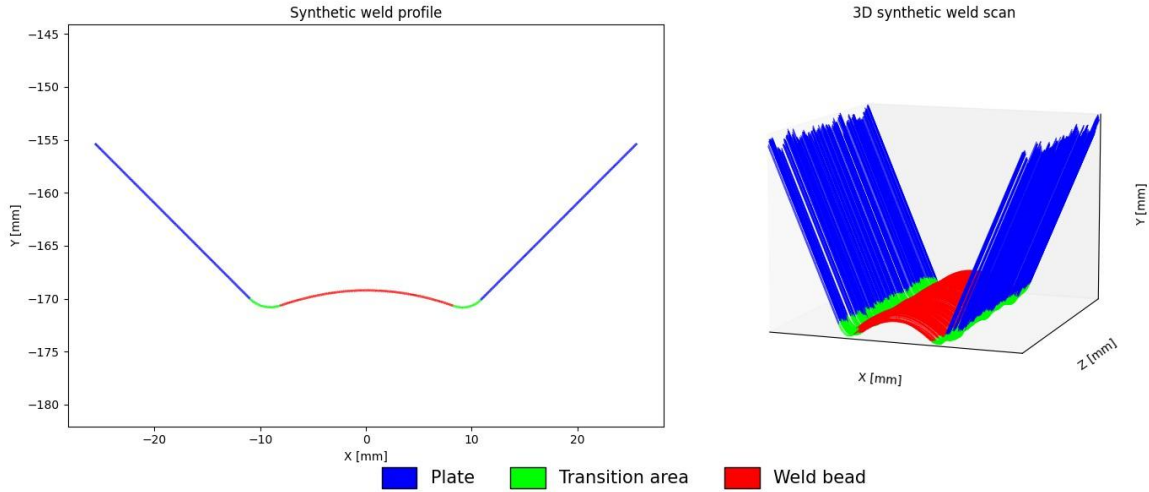


Figure 9: An annotated synthetic weld profile from a full scan.

3.2 U-net2D

3.2.1 Network & training

A two-dimensional representation of the convolutional neural network based on the U-net architecture proposed by Ronneberger et al [19] in 2015 was used in this work to classify the weld regions. The original U-net architecture was further slightly modified due to the asymmetrical spatial dimension of the training data. The primary adjustment was to keep the spatial width of the input data constant and only down sampling in the height dimension. The down sampling rate, the rate of spatial dimension decrease and channel dimension increase, was in this network set to 4 compared to the original U-net which had a rate of 2. This was to increase the receptive field and reduce the memory intensity of the network.

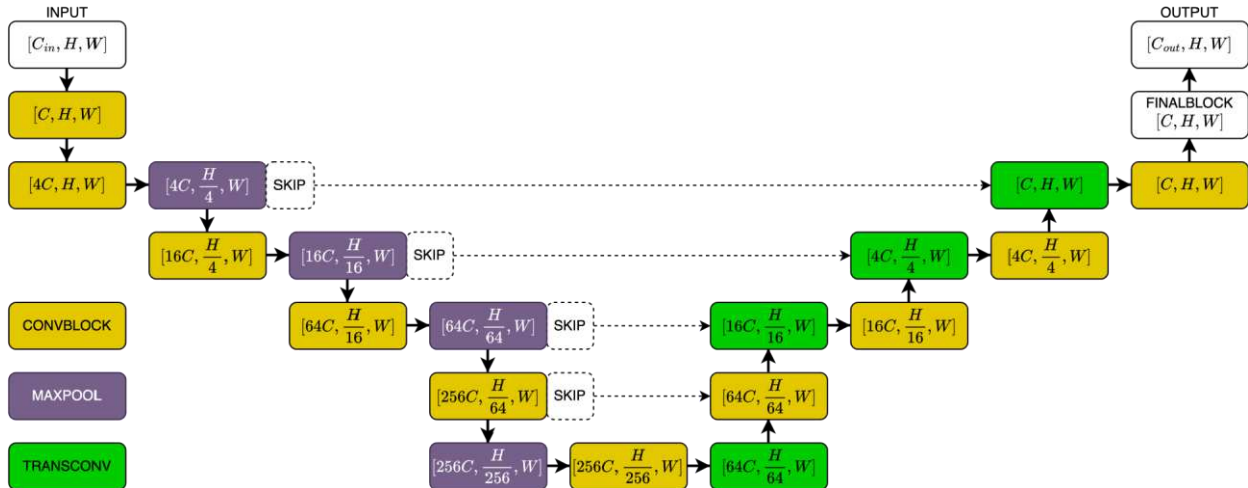


Figure 10: A conceptual figure of the network architecture with C, H and W being channels, image height and width respectively.

The architecture consisted of five different blocks. Figure 10 conceptually shows how these are connected and the output dimensions of each block. The input, final and output blocks consisted of one convolution layer designed to expand and contract the channel dimension. The convblocks used both in the expanding and contracting paths contained two convolution layers each, followed by a ReLU-activation [28]. The purpose of the maxpool blocks was to down sample the spatial dimension and only keep the pixels which were most impactful, which in the maxpool case were the ones with the highest values produced by the convblock. In contrast to maxpool blocks in the expanding path the transblocks in the contracting path were used to reduce the channel dimension and increase the spatial dimension. This was done with a transposed convolutional layer. To preserve spatial knowledge from the expanding path skip connections were added [19].

The network was trained using an AdamW optimizer [29], a Cosine annealing learning rate Scheduler [30] and a loss function using cross entropy loss [31] and a dice loss function [32]. The loss function was defined as

$$\mathcal{L} = \mathcal{L}_{CE} + (1 - \lambda)\mathcal{L}_{Dice} \quad (4)$$

where $\mathcal{L}_{CE}$ was the cross-entropy loss and $\mathcal{L}_{Dice}$ the dice loss. λ is a factor determining the impact of the dice loss. The model was trained for 50 epochs, and at each epoch, it was evaluated on the validation set. A training checkpoint was saved every 10 epochs. The loss and accuracy were saved for both datasets. This was done to evaluate and tune the hyperparameters used for training.

3.2.2 Data & preprocessing

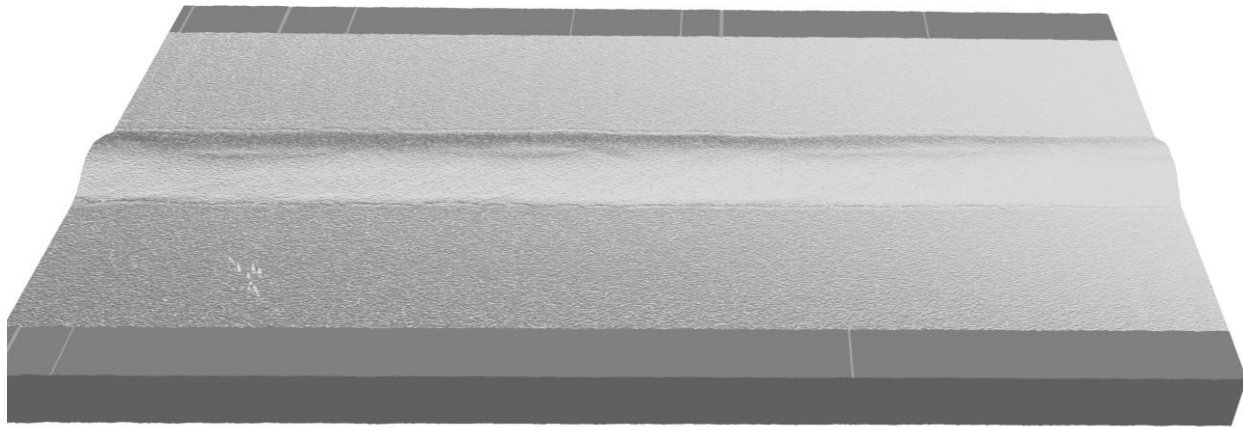
The dataset used for training the network consisted of 1000 synthetic weld-scans each, generated to mimic a scan of a 100 mm weld in either a butt or fillet configuration. To produce a network that was rotationally invariant the Cartesian coordinates produced by the synthetic scanner were converted into polar coordinates. The data in polar coordinates was sectioned into 160 profile wide images that were normalized per column using z-score normalization, as seen in equation 5 where μ and σ are the profile mean and standard deviation, to achieve profiles with a zero mean and a standard deviation of 1.

$$r_{norm} = \frac{r - \mu}{\sigma} \quad (5)$$

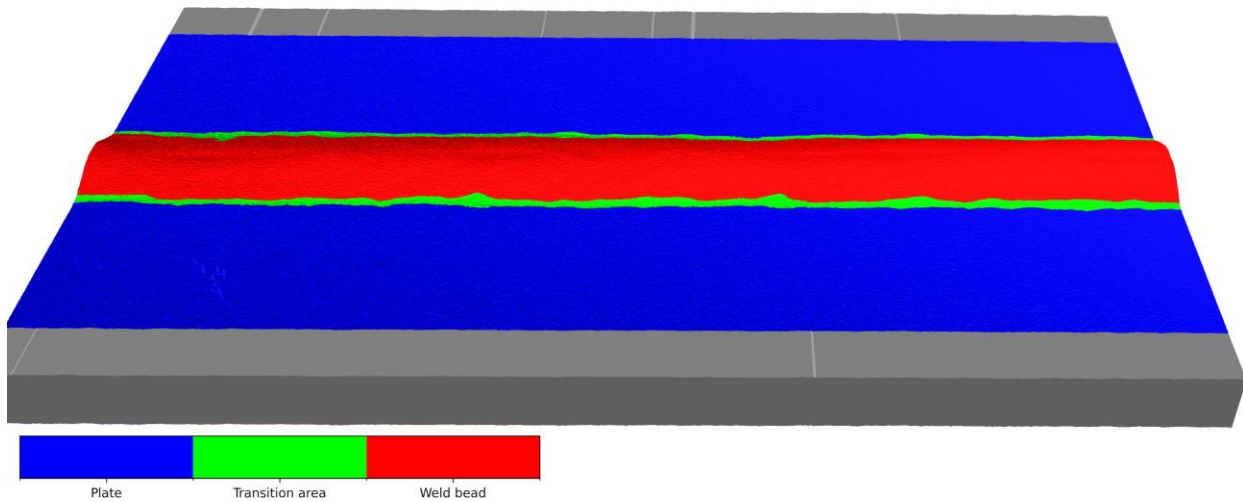
The dataset of normalized 160 profile wide images were divided randomly into a training set with 80 percent of the data and a validation set with the remaining 20 percent. During training, both datasets were used to avoid overfitting by monitoring the loss.

4. Evaluation & Result

Evaluation of the trained network was done on one butt weld and two fillet welds. One of the fillet welds was scanned with a laser scanner at a profile resolution of 2048 pixels, which was the resolution the network was trained on, and the other two welds were scanned at 1280 pixels. The 3D scans of the real-world welds can be seen in Figures 11a, 12a and 13a. The scans were evaluated using a network trained on 1000 welds, and the prediction maps were placed on top of the weld surfaces. The produced predictions seen in Figures 11b, 12b and 13b.

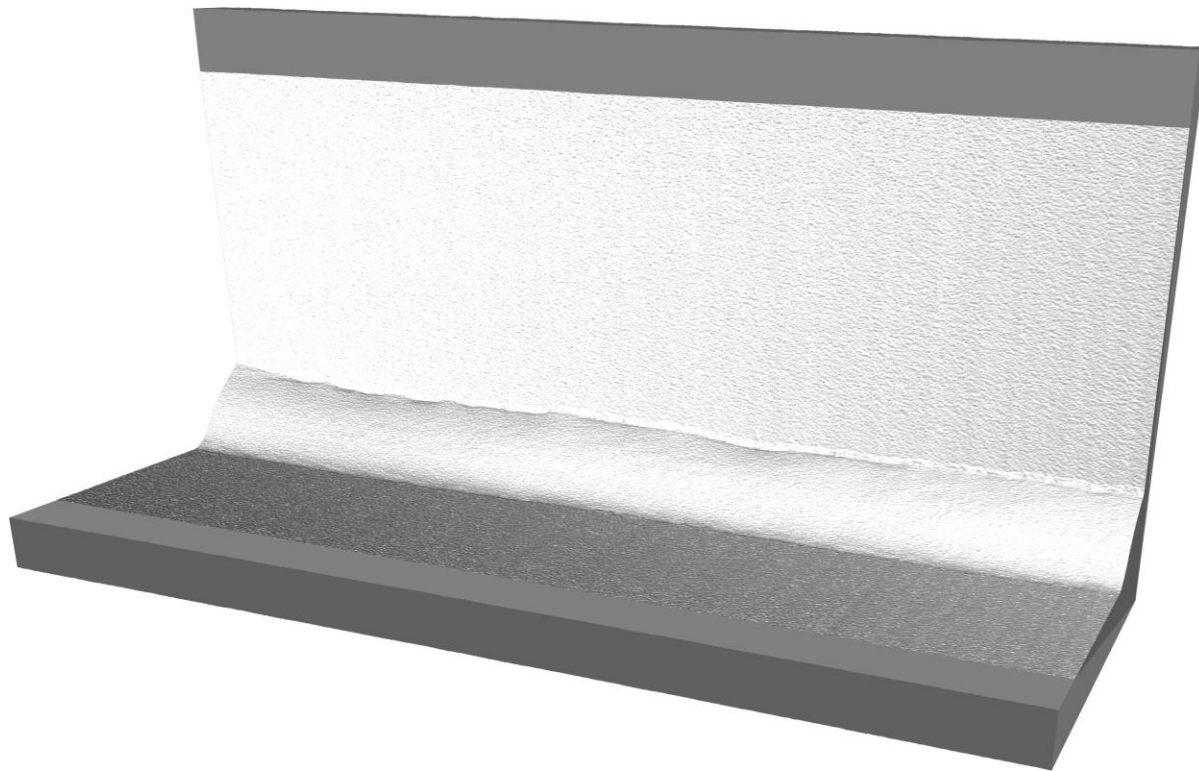


(a)

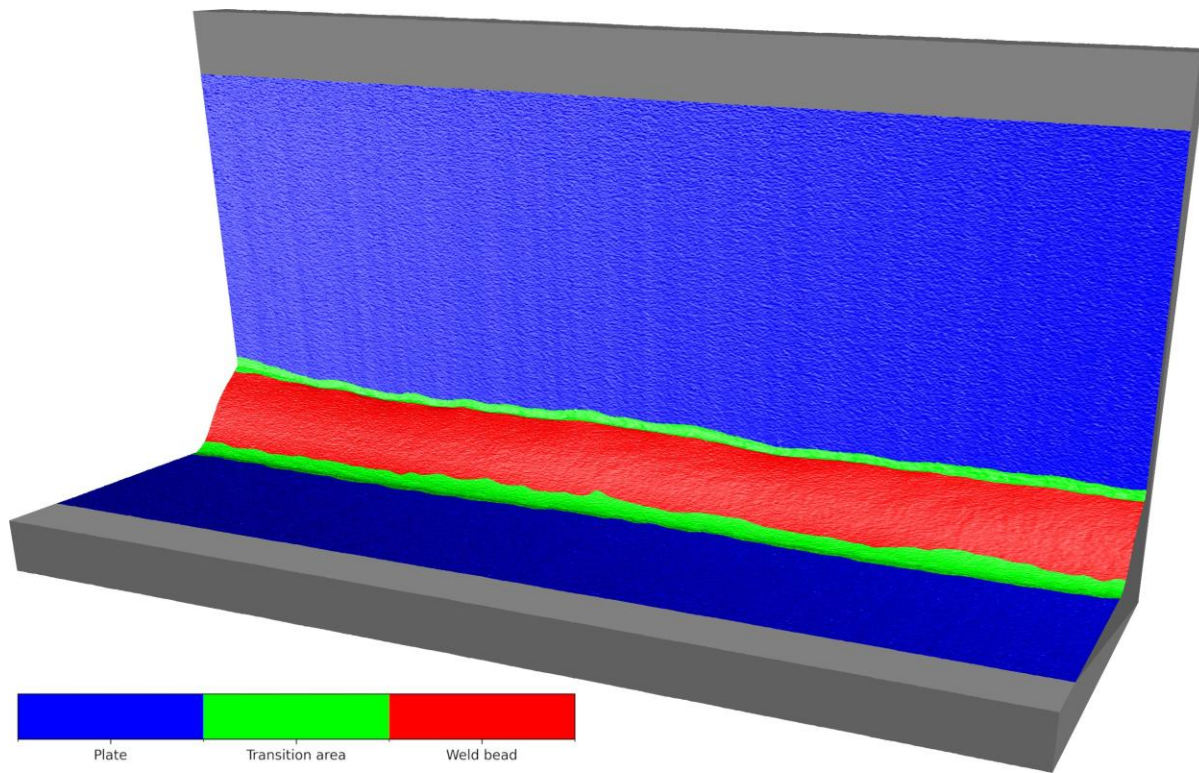


(b)

Figure 11: (a) Raw 3D scan of a butt weld at 1280-point resolution. (b) Corresponding prediction map produced by the trained network.



(a)



(b)

Figure 12: (a) Raw 3D scan of a fillet weld at 1280-point resolution. (b) Corresponding prediction map produced by the trained network.

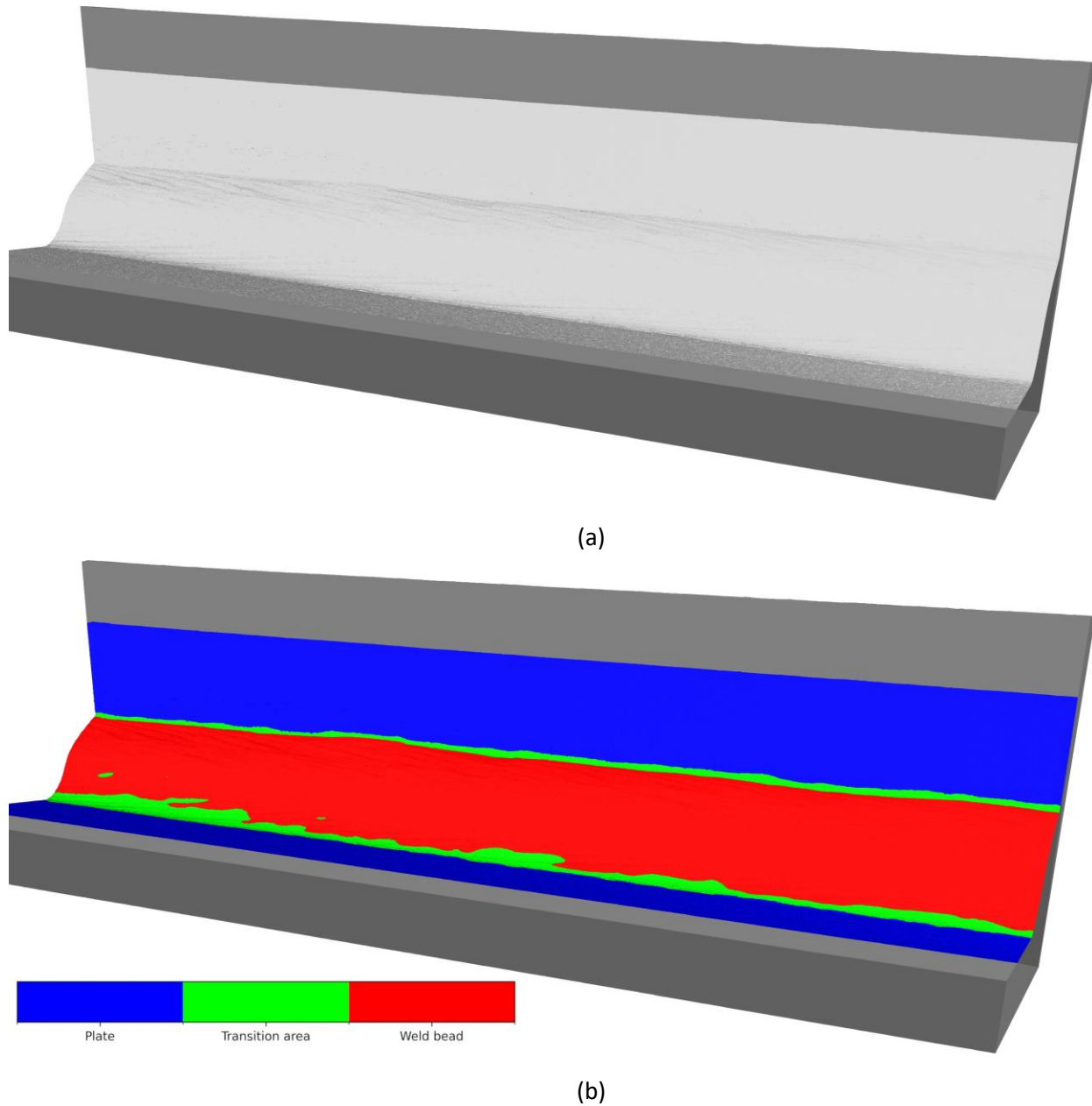


Figure 13: (a) Raw 3D scan of a fillet weld at 2048-point resolution. (b) Corresponding prediction map produced by the trained network.

5. Discussion

The main implication of weld segmentation for D-VT is its role as the first step in an automated measurement pipeline. By first identifying the transition zone, existing algorithms can operate within a considerably smaller search space when deriving weld-toe parameters such as radius and flank angle. Restricting the search space reduces the subjectivity associated with defining the weld toe location. As scanning resolutions increase, increasingly small geometric features become detectable, including ripple lines such as those towards the leftmost part of the scan in Figure 13a. If a segmentation model

can correctly identify these features as belonging to the weld bead rather than the weld toe, subsequent curve-fitting algorithms can be applied more consistently. The purpose of the neural network is therefore not to directly predict weld geometry parameters, but rather to provide a structured representation of the weld that improves existing measurement procedures, such as those described in the recent IIW best practice guidelines for D-VT [10].

This work attempts to combine the mature field of image segmentation with the emerging field of D-VT. By representing laser scan data in an image-like format, segmentation can be performed using well-established CNN architectures. The maturity of these methods provides access to robust software frameworks for data loading, optimization, evaluation, and deployment. Furthermore, CNNs exploit GPU parallelization efficiently, enabling rapid processing of large weld scans.

The primary limitation of this representation is its dependence on the characteristics of the scanning system. Both the sampling density and scanning inclination influence the geometric information available to the network. A scanner with higher spatial resolution captures finer surface details that may not be present in the training data. This could partially explain why the network performs worse on specimens scanned at a resolution of 2048 points compared to those scanned at 1280 points, as seen in Figures 12b and 13b. However, the observed performance difference may also be related to the generalization capabilities of the synthetic training data. Distinguishing between these effects requires further investigation. The scanner inclination will affect the spacing between the measured points and could potentially affect the segmentation of an unseen weld scanned with a different inclination than the one used in the training data. This issue could be resolved by either introducing many different scanner inclinations in the training data, which could easily be done with synthetic data, or utilizing the fact that CNNs have some translationally invariant features [33].

Synthetic data will always be an approximation of its real-world counterpart. The relevant question is therefore not whether a synthetic data generator can produce weld scans that are visually indistinguishable from real measurements, but whether it can reproduce the geometric and statistical characteristics required for successful classification. In this regard, synthetic data offers several advantages. It enables the generation of large quantities of perfectly annotated training samples while providing full control over weld geometry, scanner settings, and noise characteristics. Such control is difficult, if not impossible, to achieve when collecting industrial measurement data. At the same time, the synthetic generator inevitably introduces simplifications. The scanner model does not fully capture the physical measurement process, the noise model is limited, and several real-world artefacts such as weld spatter, ripple lines, oxidation, and start-stop positions are currently absent. These omissions contribute to a reality gap between synthetic and real data. Nevertheless, the results indicate that the generated data captures sufficient geometric information for the network to identify weld regions in real scans. This suggests that the network learns geometric characteristics associated with weld structures rather than merely memorizing artefacts of the synthetic generator. The remaining question is therefore not whether synthetic data can be used, but to what extent synthetic-only training can generalize to increasingly diverse real-world welds. A natural continuation of this work would be a quantitative comparison between models trained on synthetic data, real data, and combinations thereof. Such a study would help determine whether synthetic data can serve as a complete replacement for manual annotation or primarily as a means of reducing the amount of labelled real data required.

6. Conclusions

This work offers a systematic method for developing a segmentation CNN that identifies specific weld geometry regions using synthetic data. Utilizing synthetic data reduces the time-consuming and complex task of annotating real scanning data, thereby accelerating the development process of segmentation models. The study leads to the following conclusions:

- The structured point cloud data structure of laser line scanners allows weld scans to be represented as images and, by extension, enables mature image segmentation algorithms developed for computer vision applications.
- A U-net inspired neural network was shown to be capable of segmenting weld regions from laser-scanned data.
- The results show that a neural network trained on synthetic weld data can learn geometric characteristics that generalize to real measurements of welded joints, significantly simplifying the development of segmentation models.
- Weld segmentation serves as an enabler for future D-VT systems by reducing the search space for geometric determination of relevant parameters and thereby improving the repeatability of automated weld quality assessment.

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8. Dataset

In the provided GITHUB repository the material used to generate the dataset can be found. The manifest used to generate the training, and evaluation data are provided, as is the Python script for generating the data and creating new manifests.

GITHUB link: <https://github.com/Jonacarsim/Synthetic-weld-generator>

9. Statements and Declarations

The authors have no competing interests to declare that are relevant to the content of this article.

10. Author contribution

All authors contributed to the study conception.

Jonas Carlsson: Methodology, Software, Analysis & Investigation, Visualisation, Writing – Original draft.

Gustav Hultgren: Methodology, Software, Writing – Review & Editing, Supervision.

Thomas Stenberg: Software, Data collection, Writing – Review & Editing.

Zuheir Barsoum: Supervision, Writing – Review & Editing.

Joakim Jaldén: Methodology, Supervision, Writing – Review & Editing.

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