Research Article

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Bayesian optimization of single-pulse laser drilling using advanced image processing

Bayes'sche Optimierung beim Einzelpuls-Laserbohren mittels fortschrittlicher Bildverarbeitung

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Abstract: A significant challenge in laser drilling is the optimization of process parameters and drilling strategies to achieve high-quality holes. This is further complicated by the fact that quality assessment is a manual and time-consuming task. This paper presents a methodology designed to significantly reduce the manual effort required in optimizing parameters for single-pulse laser drilling of 0.3 mm thick stainless steel. The objective is to precisely drill holes with an entry diameter of 70 µm and an exit diameter of 20 µm, achieving high roundness. The features of the drilled holes were extracted automatically from the raw data. The outcomes were compared against manual measurements. Results indicate that the mean deviations between automated and manual measurements for both inlet and outlet diameters are less than 1.5 µm. Based on the results of the feature extraction, we employed a Bayesian optimization algorithm to efficiently explore the parameter space without the need for incorporating expert knowledge. The approach rapidly identified optimal drilling parameters after only a few iterations, significantly expediting the optimization process and considerably reducing manual labor.

Keywords: laser drilling; semantic segmentation; feature extraction; Bayesian optimization

Zusammenfassung: Eine wesentliche Herausforderung beim Laserbohren besteht in der Optimierung von Prozessparametern zur Erzeugung hochwertiger Bohrungen. Die Qualitätsbewertung erfolgt bislang zudem überwiegend manuell und ist daher sehr zeitaufwendig. In dieser Arbeit wird eine Methodik vorgestellt, die den manuellen Aufwand bei der Optimierung von Parametern für das Einzelpuls-Laserbohren von 0,3 mm dickem Edelstahl erheblich reduziert. Ziel war es, Bohrungen mit einem Eintrittsdurchmesser von 70 µm und einem Austrittsdurchmesser von 20 µm bei hoher Rundheit präzise herzustellen. Die Merkmale der gebohrten Löcher wurden automatisch aus den Rohdaten extrahiert und mit manuellen Messungen verglichen. Die Ergebnisse zeigen, dass die mittleren Abweichungen zwischen automatisierten und manuellen Messungen sowohl für den Eintritts- als auch für den Austrittsdurchmesser weniger als 1,5 µm betragen. Basierend auf den Ergebnissen der Merkmalsextraktion wurde ein Bayes'scher Optimierungsalgorithmus eingesetzt, um den

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Parameterraum effizient und ohne Einbeziehung von Expertenwissen zu durchsuchen. Der Ansatz identifizierte geeignete Bohrparameter bereits nach wenigen Iterationen, beschleunigte den Optimierungsprozess und reduzierte den manuellen Aufwand deutlich.

Schlüsselwörter: Laserbohren; semantische Segmentierung; Merkmalsextraktion; Bayes'sche Optimierung

1 Introduction

The manufacturing industry is constantly searching for advanced methods to improve the precision and efficiency of laser drilling processes [1]. Various strategies have been employed, including traditional methods such as Design of Experiments (DoE) and Response Surface Methodology (RSM), as well as advanced computational techniques. For instance, Gupta et al. demonstrated RSM's utility in optimizing hole quality for millisecond-pulsed lasers, yet such methods require exhaustive parameter iterations and fail to scale effectively in high-dimensional spaces [2]. Advanced computational techniques, such as artificial neural networks applied to ns-pulsed laser drilling in stainless steel (Wang et al. [3]) and neuro-fuzzy systems for predicting laser drilling outcomes (Chatterjee et al. [4]), improve prediction accuracy but remain constrained by their reliance on large training datasets and limited ability to dynamically explore complex parameter landscapes. These shortcomings highlight a critical need for optimization frameworks that minimize experimental overhead while maximizing adaptability to multidimensional parameter interactions.

Advances in computational techniques, particularly approaches to Bayesian optimization (BO), provide a promising alternative that can predict multi-dimensional parameters spaces in laser processes with significantly fewer iterations and less manual intervention [5]. Yang et al. [6] applied BO to improve taper and drilling time in spiral drilling of stainless steel, achieving suitable results with few iterations. Bamoto et al. [7] optimized a femtosecond laser micro-drilling process. Menold et al. [8] demonstrated the versatility of BO in optimizing laser cutting, laser welding and laser polishing. They showed that less experiments are needed than with traditional approaches.

In addition to the actual optimization of drilling parameters, the extraction of the features required by the optimization approaches represents a significant challenge in process optimization. In previous studies on laser drilling, the quality measurements were predominantly assessed through manual measurements [2]. Feuer et al. [9] propose an automated approach to extract the drilling geometry as features. Approaches to automated feature extraction and quality control for a laser welding process using semantic segmentation are presented by Hartung et al. [10].

This paper presents an approach that incorporates sophisticated feature extraction techniques that employ a combination of deep learning models and conventional image processing methods to accurately extract quality features of single-pulse drilled holes. Subsequently, this study investigates the potential of BO with the aim of determining optimal laser parameters including pulse power, pulse length, and focus position to ensure high-quality holes in terms of diameter and roundness.

2 Materials and methods

This section outlines the experimental setup for single-pulse laser drilling of thin metal sheets and provides an overview of the feature extraction and parameter optimization methods employed. The iterative optimization process is illustrated in Figure 1.

The optimization begins with the generation of initial parameter sets. For the initial $n = 6$ optimization steps, parameter sets are generated using a Sobol sequence [11] to ensure uniform distribution across the parameter space. Beyond these initial steps, subsequent parameter sets are determined using Bayesian optimization (BO).

The iterative process commences with the laser drilling procedure, where thin metal sheets are drilled under varying laser parameters. Following this, microscope images of the drilled inlets and outlets are captured. These images undergo analysis using a feature extraction method to quantify key quality parameters: inlet diameter d_{I}, outlet diameter d_{O}, and roundness R. The extracted quality parameters are then used as input of a cost function, which evaluates the performance of the current parameter set by deriving a cost value. This cost value serves as the input for Bayesian optimization, which subsequently suggests new laser parameters, including peak power P_{P}, pulse length t_{P}, and focus position z_{f}. This iterative process continues until predefined optimization criteria are met, ensuring systematic refinement of laser drilling parameters for improved quality and precision.

2.1 Experimental setup

Figure 2 shows the experimental setup of the single-pulse laser drilling process. In this study, a continuous wave (cw) single mode fiber laser (TRUMPF TruFiber 2000) was used to perform the single-pulse laser drilling experiments. The

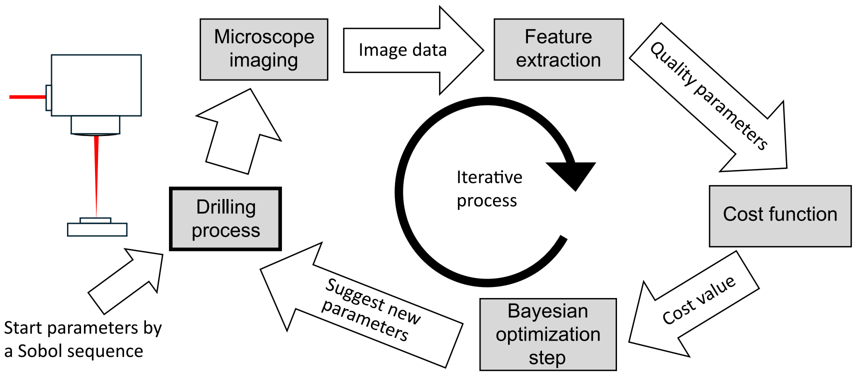

Figure 1: Iterative optimization process using feature extraction from microsocope images and a Bayesian optimization step to optimize drilling parameters.

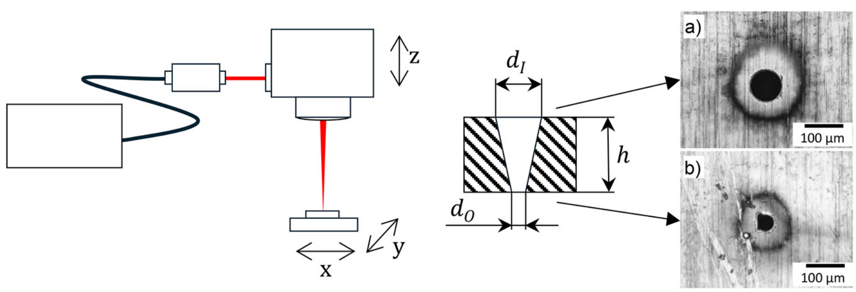

Figure 2: Left: Experimental setup. Right: Borehole cross section with images of an (a) inlet with diameter d_I and (b) outlet with diameter d_O.

emission wavelength of the unpolarized laser was specified as 1,075 nm in conjunction with a beam propagation factor of $M^2 < 1.2$. The laser beam was positioned onto the stainless steel sample with a galvanometer scanner. A telecentric F-Theta lens with a focal length of 163 mm was used, resulting in a focus diameter ($1/e^2$) of $d_f = 20$ µm. The pulsed operation mode of the laser source enables the generation of pulses with a peak power P_P up to 1,400 W. This allows for the adjustment of the pulse length between values from 1 to 25 µs. The setup was equipped with linear stages (x,y) for the sample and a linear drive (z) for the process optics to adjust the focus position. The focus position can thus be positioned with an accuracy of 1 µm.

The materials used for the experiments are stainless steel (1.4310) substrates. The substrates, with a thickness h of 0.3 mm, were cut to a size of 100 mm × 50 mm. An optical microscope (Zeiss Axio Imager) was used to evaluate the borehole criteria, such as inlet (Figure 2a) and outlet (Figure 2b). A 20× magnification was used for optical microscopic observation, where one pixel is equivalent to 0.172×0.172 µm². The evaluation criteria include the diameter of the inlet d_I and of the outlet d_O, as well as the roundness R of the outlet. We drilled and analyzed $i = 3$ holes per parameter set to reduce the influence of side effects from the inherent noise of laser processing and other uncertainties.

2.2 Feature extraction

In the context of manual measurement, the borehole diameter is determined through the use of the Menger Curvature [12]. The Menger Curvature (MC) quantifies the curvature of a triplet of points in an n-dimensional Euclidean space. It is defined as the reciprocal of the radius of the circle that passes through three points p_1, p_2, and p_3, as illustrated in Figure 3(a).

For the given borehole image, the problem is treated as two-dimensional, with p_1, p_2, and p_3 representing three non-collinear points (as shown in Figure 3(b)) in the 2D Euclidean space E^2. As shown in Figure 3(a), MC on p_2 is calculated as:

$$MC(p_1, p_2, p_3) = \frac{1}{r} = \frac{2 \cdot \sin(\varphi)}{\|p_1, p_3\|}, \tag{1}$$

where r denotes the radius of the circumcircle, $\|p_1, p_3\|$ represents the Euclidian distance between points p_1 and p_3, and φ is the angle at vertex p_2 formed by p_1, p_2, and p_3 [14]. The angle φ can be determined using the Law of Cosines.

$$\cos(\varphi) = \frac{\|p_1, p_2\|^2 + \|p_2, p_3\|^2 - \|p_1, p_3\|^2}{2 \cdot \|p_1, p_2\|^2 \cdot \|p_2, p_3\|^2}. \tag{2}$$

The three points p_1, p_2, and p_3, which are suitable to determine the Menger Curvature that assigns a reasonable

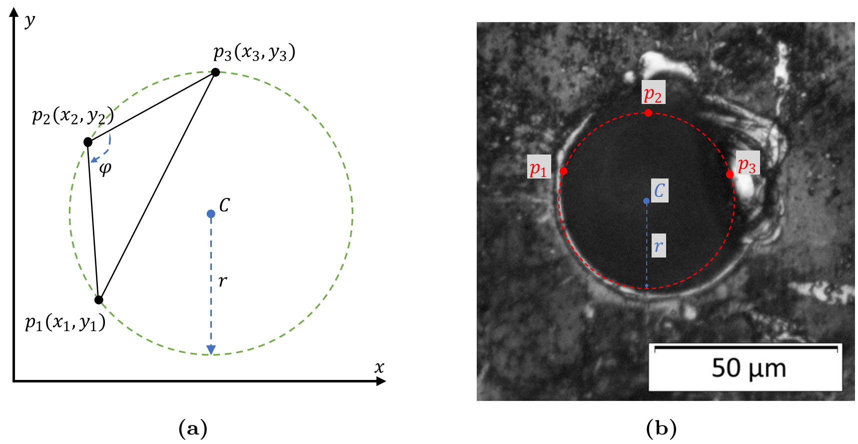

Figure 3: Manual measurement of the borehole diameter (a) The Menger Curvature of a triple of data points on a 2-D space, based on Zuo et al. [13]. (b) Example of radius determination using the Menger Curvature on a borehole.

radius to the borehole, are currently determined manually by process experts by inspecting calibrated images of the boreholes. This method is not only time-consuming but also prone to variability, both among different experts and within repeated measurements by the same expert, due to inconsistencies in the placement of the measurement points.

The objective is to automatically extract the features that are required for the parameter optimization directly from the microscope images. The features include the borehole's inlet diameter d_I and outlet diameter d_O, the borehole's roundness R, the area of the melt deposits around the borehole, and a classification of whether a breakthrough has occurred. Initial attempts to perform feature extraction based solely on conventional image processing methods have not delivered satisfactory results. Due to the divergent surface properties of the materials to be processed, there is a high degree of variance in the captured images, for example, due to reflections and mirroring. This variance requires great efforts to manually adjust the algorithm parameters of conventional image processing methods. Deep learning methods represent another viable approach to address natural deviations in images like reflections and mirroring. However, a method based exclusively on deep learning that directly determines quality characteristics can be intricate and challenging for operators to understand. A combined approach, comprising semantic segmentation models and conventional image processing methods, enables a more robust and understandable extraction of features. In our study, we employ two semantic segmentation models, each with a neural network architecture modified from the SDU-Net [15]. Our approach builds directly on principles established in the foundational U-Net architecture by Ronneberger et al., which demonstrated successful segmentation results with only 30 annotated training samples [16]. The SDU-Net architecture enhances the original U-Net design by incorporating stacked dilated convolutions, which expand the receptive field without increasing the number of parameters [15]. Additionally, we employ *Categorical Focal Loss* [17] to mitigate overfitting in class-imbalanced scenarios by focusing learning on hard-to-classify examples, ensuring robust performance even with limited data. These models are used to segment images from the top (inlet) and bottom (outlet) of the borehole. The inlet model classifies the image into the following classes, as partly shown in Figure 4(b): *burr*, *melt deposits*, and one of the classes *borehole with breakthrough* or *borehole without breakthrough*. The outlet model segments the image into: *background*, *melt deposits*, *borehole with breakthrough*, and *borehole without breakthrough*. To train the inlet model, 68 labeled images were used, while the outlet model was trained with 44 images. The discrepancy in the number of training images is because only through boreholes are included in the outlet dataset. The models are initialized randomly without any pre-training. The classes segmented by the models are further analyzed using conventional image processing methods. Figure 4(c) shows, how the borehole diameter d_I was calculated using the contour (green) of the segmented borehole class *borehole with breakthrough*. This calculation involves averaging the diameters of two specific circles: the minimum enclosing circle, $d_{min,enc}$ (shown in yellow), determined using the method proposed by Welzl et al. [18], and the maximum inscribing circle, $d_{max,ins}$ (shown in red), as described by Xia et al. [19].

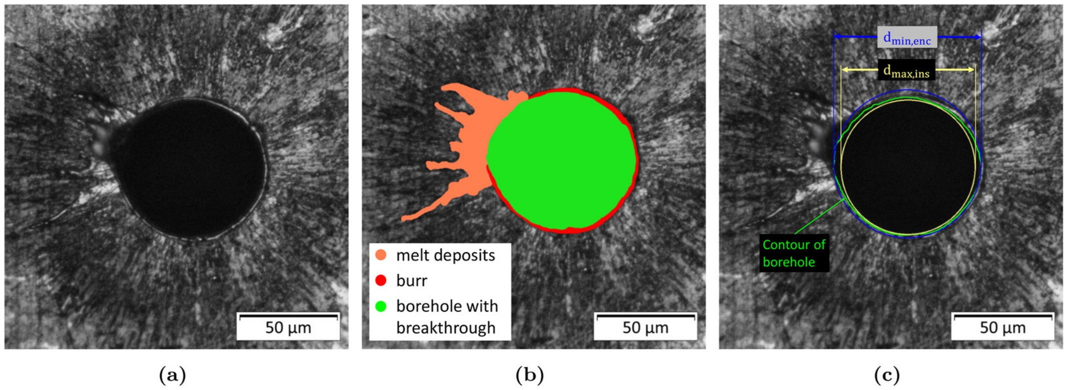

Figure 4: Feature extraction approach. (a) Inlet of a borehole with breakthrough. (b) Segmented classes by the neural network: melt deposits, burr, and borehole with breakthrough. (c) Contour of the borehole (green) from which the diameter of the maximum inscribing circle $d_{\text{max,ins}}$ (yellow) and the diameter of the minimum enclosing circle $d_{\text{min,enc}}$ (blue) were derived.

The roundness R of the borehole is defined by the ratio of the borehole area A_{borehole} (Figure 4(b) green) to the area of the minimum enclosing circle $A_{\text{min,enc}}$ [20]:

$$R = \frac{A_{\text{borehole}}}{A_{\text{min,enc}}} \tag{3}$$

This equation provides a quantitative measure of roundness, enabling straightforward comparisons between different boreholes. The method is applicable to boreholes that are shaped irregularly, as shown in Figure 5, ensuring that deviations from perfect circularity are effectively captured by employing the minimum enclosing circle. Furthermore, the use of the minimum enclosing circle ensures that the largest possible deviation from roundness is considered, offering a conservative assessment of circularity. The method's sensitivity to outliers, such as melt deposits as shown in Figure 5(c), is a notable characteristic. These irregularities can disproportionately influence the area of the minimum enclosing circle, thereby distorting the roundness value. However, this high sensitivity to outliers is not inherently disadvantageous, as such irregularities directly impact the quality of the borehole. Consequently, high sensitivity is a desirable characteristic in this context, as it accentuates deviations that could compromise the functionality or structural integrity of the well.

The melt deposition area is calculated as the sum of the segmented burr and melt deposits area classes. In order to ascertain whether breakthrough is present, the areas belonging to the *borehole with breakthrough* and *borehole without breakthrough* classes are compared. A breakthrough is classified if the area of the *borehole*

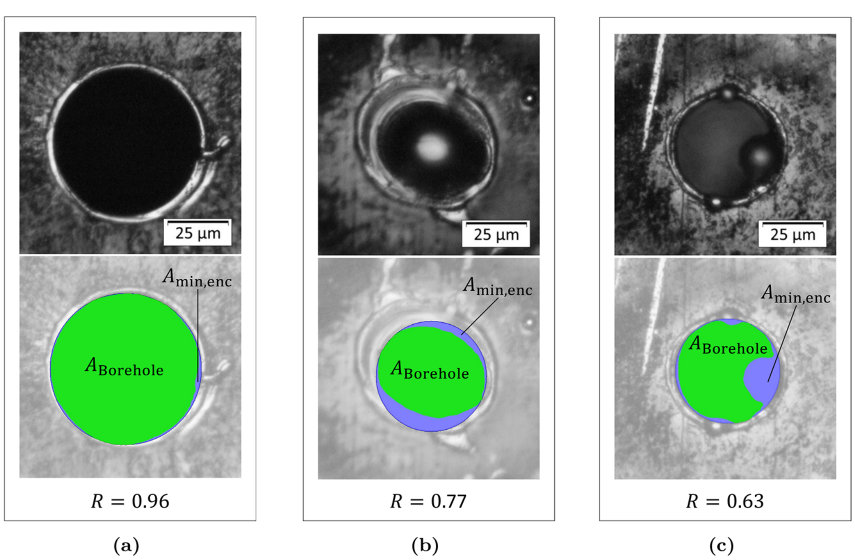

Figure 5: Illustrations of the minimum enclosing area ($A_{\text{min,enc}}$, blue) for various borehole geometries (A_{borehole}, green) with results for roundness values R.

with breakthrough class is larger than that of the *borehole without breakthrough* class. Otherwise, no breakthrough is classified.

2.3 Bayesian optimization

To optimize the single-pulse laser drilling process, we used extracted process and quality data in a Bayesian optimization framework to identify optimal laser parameters. The AX Service API [21] was used, with a Gaussian Process as a surrogate model [22], and the default *Matern 5/2 kernel* for the optimization. This approach efficiently explored the parameter space, aiming to optimize the drilling process with minimal experimental effort. As acquisition function *Expected Improvement* [23] was used. The choice of these Bayesian Optimization parameters is derived from the comprehensive research results by Menold et al. [8], who demonstrated their effectiveness across various other laser processes.

2.3.1 Process parameters and quality variables

Holes drilled with laser usually need to fulfill requirements regarding dimensional accuracy, surface quality and reproducibility. For this paper, we concentrated on optimizing three quality variables: (1) inlet diameter d_I, (2) outlet diameter d_O and (3) roundness R by varying the process parameters pulse power P_P, pulse length t_P and the focal position z_f as listed in Table 1. The aim was to achieve a target inlet and outlet diameter d_{target}, and at the same time, the greatest possible roundness $R_{target} = 1$ at the outlet. The quality variables result from the feature extraction process described in Section 2.2. The area of the melt deposits was excluded from the BO to concentrate on enhancing the accuracy of the geometrical features.

2.3.2 Cost function

In order to compare the quality of different boreholes, a cost function $C(\mathbf{x})$ was formulated that converts the characteristic quality variables into a comparable cost value. The aim of the Bayesian optimization method is to minimize the cost value

$$C(\mathbf{x}) = w_{d,I} \cdot |d_I(\mathbf{x}) - d_{I,target}| + w_{d,O} \cdot (d_O(\mathbf{x}) - d_{O,target})^2 + w_R \cdot (1 - R(\mathbf{x})) + w_E \cdot E_P \tag{4}$$

by iteratively adjusting the process parameters $\mathbf{x} = (P_P, t_P, z_f)$ to achieve a target inlet and outlet diameter with maximum roundness of the outlet.

In the cost function, each of the three quality variables is represented by a summand. Each of these summands increases with increasing deviation between the variable's value and the target value. A fourth summand refers to the pulse energy E_P by multiplying pulse length and pulse power $E_P = P_P \cdot t_P$, which is to be minimized to encourage a short drilling duration and lower heat input. The quality characteristics are prioritized using weights w_i. Determining the appropriate weights requires domain-specific expertise and is inherently subjective. These weights are contingent upon the optimization objectives and the relative magnitude of the associated process parameters. Given the significant impact of the weights on the optimization outcomes, it is necessary to adjust them prior to initiating the optimization process.

The weights were kept constant as $w_{d,I} = 1\,\mu m^{-1}$; $w_{d,O} = 4\,\mu m^{-1}$; $w_R = 200$; $w_E = 2\,mJ^{-1}$. For each iteration n, three holes were drilled using the parameter set $\mathbf{x}_n$ and evaluated with an optical microscope. The image data was analyzed by feature extraction as described above. If no breakthrough occurs, the cost C becomes high due to the quadratic influence of the outlet diameter term $w_{d,O} \cdot (d_O(\mathbf{x}) - d_{O,target})^2$. In addition, the roundness R is set to zero, which leads to maximum costs of the roundness term $w_R \cdot (1 - R(\mathbf{x})) = 200$.

Table 1: Process parameters and quality variables.

Category	Parameter/ variable	Symbol	Value range, target
	Pulse power	P_P	300 W … 1,400 W
Process parameters	Pulse length	t_P	1 µs … 25 µs
	Focal position	z_f	−200 µm … 200 µm
	Inlet diameter	d_I	$d_{I,target} = 70$ µm
Quality variables	Outlet diameter	d_O	$d_{O,target} = 20$ µm
	Roundness	R	0 … 1, $R_{target} = 1$

3 Results and discussion

This section discusses the results obtained from the feature extraction techniques, which are divided into two parts: The evaluation of the training of the segmentation networks and the evaluation of the feature extraction methods based on the segmentation results. Subsequently, we explore the findings from the BO.

3.1 Results of the feature extraction

The effectiveness of the feature extraction was evaluated by measuring 75 inlets and outlets, which were then compared with the results of a manual measurement conducted by experts. These images were not included in the training data set. We employ the Intersection over Union

$$\mathrm{IoU}(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{5}$$

introduced by Jaccard et al. [24] as an evaluation metric to assess the predictions of the model. Here A is the segmentation mask used for training and B is the prediction of the segmentation network. During the evaluation, the inlet model achieved an IoU value of 0.97 for the borehole classes, while the outlet model achieved an IoU value of 0.95 for this class. However, the melt deposits and burr classes exhibit a decline in performance, each reaching an IoU value of 0.75. This can be attributed primarily to the distinctive characteristics of the melt deposits, which also leads as a maximum IoU value of 0.78 for these two classes during training.

After image segmentation, diameters are calculated based on the prediction of the borehole models. To assess the precision of the measurement techniques with respect to representative data, the inlets and outlets of 75 additional boreholes, drilled in identical experimental conditions as illustrated in Figure 2, were evaluated. The measurements were performed using two methods: automatic feature extraction and manual measurements based on the Menger Curvature method. Each of the 75 boreholes was measured manually by two experts (Person A and Person B), with Person A performing two independent measurement trails for all 75 boreholes. Table 2 presents the mean values of inlet and outlet diameters for each measurement method. The distribution of inlet and outlet diameters, along with respective deviations between measurements, is shown in Figure 6.

Table 2: Mean values of 75 measured inlet and outlet diameters of automatic feature extraction and manual measurements by experts.

Diameter	Feature extraction	Person A, first trial	Person A, second trial	Person B
Inlet	71.44 µm	71.08 µm	71.45 µm	72.47 µm
Outlet	28.47 µm	27.86 µm	27.96 µm	27.43 µm

The mean deviation between Person A's first trial and the automated measurement trial is 0.36 µm for inlet diameters and 0.61 µm for outlet diameters, which is within the expected accuracy and tolerance limits for borehole measurements. The mean deviation between manual measurements conducted by Person A (first trial) and Person B is 1.39 µm for inlet diameters and 0.43 µm for outlet diameters. These low deviations across all automated and manual measurement techniques validate the effectiveness of feature extraction in determining inlet and outlet diameters. The methods outlined enable automated borehole measurement, facilitating parameter optimization while significantly reducing manual effort.

3.2 Results of the Bayesian optimization

Figure 7 shows the evolution of the process parameters (left) and quality variables (right) during the optimization process. During the initialization process (orange) with parameters chosen by the Sobol sequence, a wide range of process parameters is covered, resulting in a high cost value (red curve). In the start sequence, three parameter sets $n = 3, 4, 5$ did not lead to through holes, because the pulse length was too short. In the following optimization steps the BO suggested only one more parameter set at $n = 26$, where no breakthroughs were achieved.

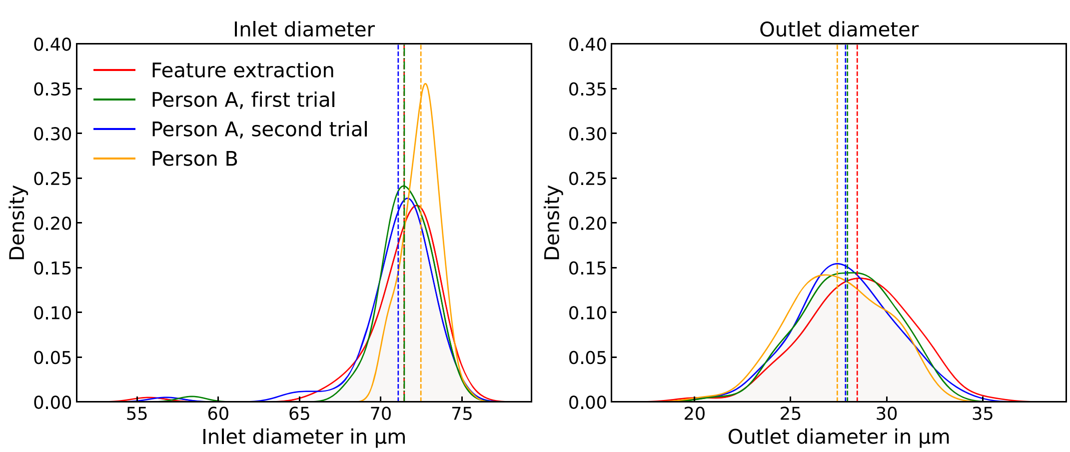

Figure 6: Comparison of measurement methods for 75 measured borehole inlets and outlets. Distribution of inlet (left) and outlet (right) diameters and their mean value by using automatic feature extraction and manual measurements.

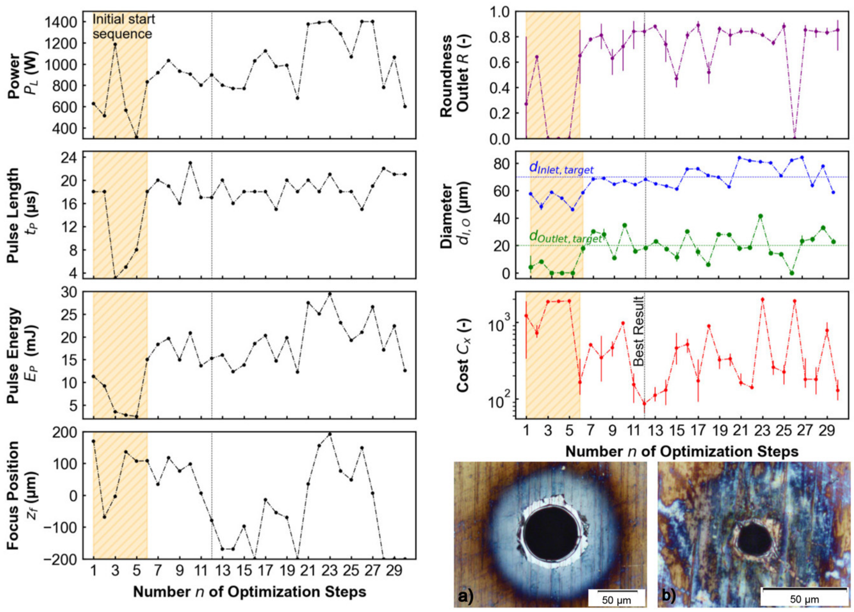

Figure 7: Results of Bayesian optimization process. Left: Evolution of process parameters (focal position, pulse power, pulse length) over 30 iterations. Right: Corresponding quality variables (inlet diameter, outlet diameter, roundness) and cost function value. Orange points indicate initialization phase. Insets (a) and (b) show inlet and outlet of optimal borehole at iteration $n = 12$.

In the bottom right of Figure 7 the inlet and outlet of the borehole with the minimum cost value $C_{12} = 86.00$ after $n = 12$ iterations with process parameters $z_f = -79.0$ µm, $P_L = 898$ W and $t_P = 17$ µs is shown. This led to an inlet diameter of $d_I = 68.0$ µm, an outlet diameter of $d_O = 18.03$ µm and a roundness of $R = 0.84$ which are close to the targeted values.

4 Conclusions

The aim of this work was to reduce the manual effort in parameter search for single-pulse laser drilling. By employing a combination of deep learning techniques for the segmentation of microscope images and conventional image processing methods for the measurement of segmentations, it is possible to perform a robust and rapid determination of the quality features of a borehole, particularly in challenging imaging situations, such as those caused by reflections. The results demonstrate that the mean deviations between manual measurements and feature extraction for both inlet and outlet diameters are less than 1.5 µm. It has been shown that the deviation between manual and automated measurement is smaller than between two manual measurements carried out by different persons.

Furthermore, Bayesian optimization has been demonstrated to be an effective approach for achieving target hole characteristics with a minimal number of iterations. In an optimization experiment comprising 30 iterations, the parameters conducive to drilling with the desired characteristics were identified after just 12 iterations. This significantly reduces the need for traditional full-factorial experimental designs, simplifying the laser drilling optimization process and increasing efficiency in industrial applications.

Future research directions include the development of hybrid models that combine Bayesian optimization with physics-informed constraints to further reduce experimental iterations, validation of the presented procedure for additional use cases, and investigation and optimization of computational efficiency.

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Data availability: The data that support the findings of this study are not publicly available due to confidentiality restrictions.

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