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Definition of requirements for robust seam-tracking in robotic laser welding applications

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Abstract

The increasing adoption of robotic laser welding highlights the need for robust seam-tracking systems to ensure precision and adaptability. Current methods struggle with fixturing errors, part-to-part variations, thermal deformation and the need for precise alignment of the laser beam, especially in three-dimensional welding scenarios. Laser welding is particularly sensitive to variations in joint morphology and material reflectivity, requiring advanced solutions to maintain high welding quality. Spatial beam shaping techniques, based on beam oscillation or "wobbling", partially mitigate these issues by accommodating variable joint gaps and high-reflectivity materials. However, solutions, capable of real-time trajectory planning and adaptive process control, are essential to meet the requirements of this technology. This work presents a comprehensive analysis of the technological and computational requirements for seam-tracking operations, providing a foundation for developing systems capable of operating at high welding velocities, while ensuring quality and minimizing rework, paving the way for a more-effective implementation in smart-manufacturing.

Keywords: Robotic Laser Welding; Seam-Tracking; Spatial Beam Shaping; Real-Time Process Monitoring

1. Introduction

Robotic laser welding is rapidly emerging as a cornerstone of advanced manufacturing owing to its high precision, concentrated energy delivery and ability to join complex geometries. Its applications span on a wide range of industries, including automotive chassis production, aerospace component fabrication, shipbuilding and increasingly emerging sectors such as lightweight construction and e-mobility. Despite its advantages, laser welding poses significant challenges, mainly the requirement for extremely tight tolerances and precise relative positioning between the laser head and the workpiece. Even slight misalignments can result in weld defects or complete joint failure (Colombo et al., 2013). To mitigate such risks, preceding manufacturing steps must achieve high dimensional accuracy. In addition, the welding path is typically predefined using teach-and-playback methods, where operators manually program the robot's movements, while rigid and custom-designed fixtures are often needed to eliminate gaps between parts (Liu et al., 2009). This requirement severely limits flexibility, especially when dealing with complex geometries or small production batches (Rout et al., 2019). Ensuring accurate laser-to-seam alignment critically depends on the robot's ability to execute high-precision path trajectories. While industrial robots offer excellent repeatability, their absolute accuracy is often insufficient, particularly when executing complex trajectories involving frequent tool reorientations (Siciliano et al., 2008). Robust seam-tracking is a key enabler for improving quality and process reliability in robotic laser welding, as it ensures continuous and real-time alignment between the laser beam and the weld seam. These systems are designed to compensate for deviations caused by process dynamics, positioning inaccuracies, and part-to-part variability, thereby maintaining weld integrity and minimizing the need for post-process inspection and rework (Zou at al., 2018). Although specific requirements may vary across industries, such as high-speed throughput in automotive applications versus geometric complexity in aerospace, common performance demands include high precision, real-time responsiveness, adaptability, robustness in harsh environments, and seamless integration into existing automation and control frameworks. The real-time nature of seam tracking must contend with several sources of disturbance. Variations in joint geometry, e.g., lap, butt, or fillet joints, may arise due to machining tolerances or inconsistent fixturing. Materials like aluminum alloys introduce further complexity due to their high reflectivity, which can degrade sensor performance. Thermal distortion during welding may also cause the seam to shift from its nominal position. Moreover, environmental factors such as spatter, fumes, or plasma emissions can obscure the sensor's field of view or introduce noise into the signals.

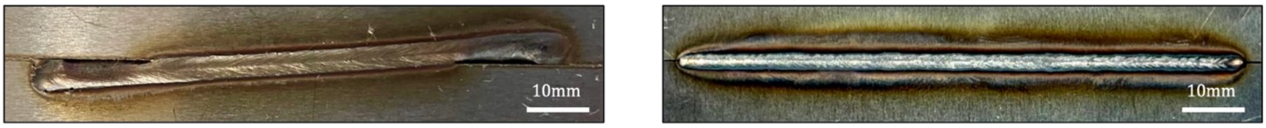
In this context, this paper proposes a unified framework for identifying and analyzing seam-tracking requirements in robotic laser welding across various industrial domains. Special emphasis is placed on vision-based seam-tracking, given its growing adoption in industry and the rapid progress of enabling technologies in computer vision and artificial intelligence (Guo et al., 2024). Seam-tracking in robotic laser welding functions as a closed-loop control system, continuously monitoring the weld seam's position and adapting the robot's trajectory in real time to maintain optimal alignment. This process integrates three essential operations: sensing, interpretation, and actuation. Sensors, whether optical, laser-based, or tactile, first acquire raw data regarding the weld joint's location and geometry. This data is then processed to extract spatial coordinates and define the actual seam path. Based on this interpretation, the control unit dynamically adjusts the robotic arm or laser parameters to follow the seam accurately. Maintaining this feedback loop at high frequencies is especially critical at elevated welding speeds.

2. Seam Tracking in Laser Welding: Challenges and Requirements

As robotic laser welding evolves to meet the demands of high-mix, high-precision production, the role of adaptive and reliable seam-tracking becomes increasingly central. The capability to maintain precise beam-to-seam alignment, despite geometric tolerances, thermal effects, and process variability, is essential across industrial manufacturing. To perform effectively across such diverse and demanding industrial scenarios, seam-tracking systems must meet a comprehensive and interrelated set of performance criteria. These requirements span spatial precision, to ensure sub-millimeter alignment of the laser beam; computational efficiency to process high-frequency sensor data with minimal latency; sensor robustness, especially for vision-based technologies that are sensitive to spatter, reflectivity, or low contrast and adaptability, to maintain consistency under varying joint geometries, materials, textures, and dynamic disturbances. This section introduces a unified analytical framework for classifying and evaluating the principal requirements for robust seam tracking in robotic laser welding. It is structured into three key domains: spatial requirements focusing on the accuracy, resolution, and dimensional robustness needed to track complex seam trajectories; computational requirements examining the processing capabilities required to interpret sensor input, filter disturbances, and apply real-time corrections and sensors requirements with a particular emphasis on vision-based systems, including image acquisition, processing strategies, and adaptability. Integration and adaptability highlighting the need for seamless interfacing with welding control architectures and consistency across variable operating conditions. By analyzing these dimensions, the framework supports the design and evaluation of tracking systems capable of meeting stringent performance targets and adapting to future advancements in real-time process control.

2.1. Spatial Requirements

In robotic laser welding, spatial accuracy is the most fundamental determinant of seam-tracking performance. The laser beam, typically with a focal diameter in the range of, 100–600 µm delivers concentrated thermal energy that must be precisely aligned with the joint centerline to avoid defects such as incomplete penetration, misalignments, or heat-affected zone (HAZ) distortion. Fig. 1(a) illustrates an exemplary case of a weld defect due to misalignment. Fig. 1(b), instead, shows a good quality weld for the same weld trajectory. This imposes strict requirements on the spatial detection, interpretation, and control precision of the tracking system. The minimum positional accuracy required lies within the sub-millimeters range, depending on the joint configuration and material thickness. Therefore, seam detection algorithms must be capable of resolving positional deviations in the micrometers domain and control systems must apply corrections with equivalent spatial resolution (Wei et al., 2024). In addition to lateral precision, accurate three-dimensional seam-tracking is increasingly critical, especially in applications involving non-planar geometries such as tubular structures or curved panels. The tracking system must resolve not only the seam's position in X and Y directions but also along the Z-axis, where precise control of the focus position of the laser beam is essential to maintain the laser beam focal point on the workpiece to be welded. Inaccuracies in the Z-axis detection can lead to defocusing, energy dispersion, and fluctuations in penetration depth, all of which compromise weld quality. Techniques such as optical triangulation are widely used for depth acquisition; however, they require meticulous calibration and remain sensitive to surface properties like reflectivity and texture (Zhou et al., 2020). Furthermore, seam-tracking must ensure trajectory stability across complex joint geometries, including curved seams and non-planar surfaces which introduce non-linear motion components that can amplify tracking error if not properly compensated in real time. Achieving this stability requires high spatial continuity in seam feature detection, particularly when navigating geometric discontinuities such as gaps, holes, pre-punctures, or fillet intersections. These features can momentarily obscure or distort the visual signature of the seam, increasing the risk of tracking loss or path deviation if not properly handled by the system's algorithms (Boldrin et al., 2024). Another key metric is the spatial resolution of the sensing system, defined by the field of view and the pixel or point density of the sensor. For example, in a structured light vision system with a $10\ \mathrm{mm}$ field of view and 1000 pixel resolution, the theoretical spatial resolution is $10\ \mu\mathrm{m}/\mathrm{pixel}$. However, practical resolution is constrained by optical noise, illumination conditions and the performance of the feature extraction algorithm (Wang, 2024). To mitigate the impact of strict spatial positioning tolerances, particularly in applications with high geometric variability or tracking uncertainty, advanced spatial beam shaping techniques, based on beam oscillation or "wobbling" are increasingly applied. Wobbling introduces a controlled oscillation in the beam path, which enlarges the effective interaction zone and increases tolerance to small seam deviations or gaps providing an additional buffer against spatial misalignment (Boldrin et al., 2024). These methods do not eliminate the need for high-precision tracking but provide a compensatory mechanism that enhances weld stability in challenging geometric conditions. Finally, the system must maintain repeatability, typically defined as the standard deviation of the seam position detected over multiple identical welds under constant conditions. In some applications a very stringent repeatability is often required like in aerospace and medical applications, where joint integrity is safety critical. In summary, the spatial requirements for seam tracking extend far beyond nominal accuracy; they encompass multi-axis precision, depth sensitivity, geometric continuity, optical resolution, and statistical repeatability. Meeting these requirements demands not only advanced sensing hardware but also precise calibration procedures, robust feature extraction algorithms, and tight integration with the robotic control system.



(a) (b)

Fig. 1 (a) Weld defect due to misalignment between the laser beam and the welding seam; (b) a good-quality weld along the same trajectory.

2.2. Computational Requirements

Effective seam-tracking relies heavily on the computational performance of the underlying processing architecture. The system must be capable of extracting seam location data from sensor inputs in real time, often at frame rates above $100\ \mathrm{Hz}$, while maintaining minimal latency to prevent delays in trajectory correction. To enhance responsiveness, predictive control strategies are increasingly adopted, utilizing machine learning models to predict seam deviations before they occur. These approaches, however, demand considerable computational resources and must be optimized to operate within the constraints of real-time execution. Additionally, the system must be able to handle sensor noise and interpolate missing data points without sacrificing responsiveness. Scalability is another critical factor, especially in advanced welding scenarios where multiple seams or dynamic conditions are present. Processing sensor data, particularly from high-resolution vision systems, requires consistent analysis with total processing latency kept within a few milliseconds. Any deviation beyond this can cause delayed corrections, misalignment of the laser beam, and consequent welding defects. To meet these stringent demands, algorithms must efficiently detect, localize, and extract seam features, then quickly translate them into corrective actions. Traditional image processing methods such as grayscale analysis or edge detection are increasingly being complemented, or replaced, by AI and deep learning techniques, due to their superior generalization capabilities across various joint geometries, surface finishes, and harsh visual environments. Achieving real-time performance with deep learning requires the use of lightweight neural architectures and models tailored to the computational hardware. In 3D seam tracking scenarios, such as those utilizing stereo vision or laser triangulation, the computational demands rise significantly due to the large volume of data that must be processed and interpreted. To manage this complexity, strategies like voxel-based downsampling and hierarchical (coarse-to-fine) segmentation are often applied. These techniques help reduce redundant information and accelerate computation while maintaining essential seam characteristics. For example, Wei et al. (2024) demonstrated that such methods can substantially lower processing time, making real-time performance feasible also in these cases. A critical enabler of high-performance seam tracking is the use of dedicated computational hardware, particularly graphics processing units (GPUs). The parallel processing capabilities of GPUs significantly accelerate tasks such as convolutional operations in deep neural networks, real-time segmentation, and depth map generation in vision systems. For industrial deployment, GPU-accelerated edge computing platforms (e.g., NVIDIA Jetson, Xavier) are commonly integrated into robotic controllers to offload computational load from central processing units and meet the latency constraints required for in-process adaptation. This hardware integration is essential for achieving stable, high-speed performance in vision-based seam tracking under production constraints. Finally, computational reliability and fault tolerance are essential in industrial deployment. Systems must continue operating under partial sensor failure, wrong data interpretation and communication noise without loss of tracking. This requires integrated diagnostics, fallback mechanisms, and redundancy in both hardware and software components. In sum, the computational requirements for robust seam-tracking encompass not only speed but also algorithmic efficiency, resource adaptability, predictive capability, and system resilience, each of which contributes to the overall precision and reliability of robotic laser welding operations in demanding manufacturing contexts.

2.3. Sensor Requirements: Vision-Based Systems

Among the various sensor technologies used for seam-tracking, vision-based systems are particularly attractive due to their flexibility, cost-effectiveness, and high flexibility in capturing detailed spatial information about weld seams. However, their performance is highly dependent on several factors. First, the image acquisition system must maintain high resolution and contrast under difficult lighting and environmental conditions, including the presence of weld spatter or process light. A primary requirement is high-fidelity image acquisition under challenging welding conditions. Laser welding processes generate intense light, spatter, fumes, and plasma, which can degrade image quality. To counteract these effects, systems often employ structured illumination, bandpass filters, and protective enclosures. High dynamic range (HDR) sensors and synchronized lighting systems are also utilized to maintain visibility of seam features across various surface conditions. The robustness of image processing algorithms is equally critical. Traditional edge detection methods may falter under low-contrast or contaminated conditions. Consequently, modern systems leverage deep learning-based segmentation and detection networks, which have demonstrated enhanced generalization across seam geometries and surface states. These algorithms must operate at inference speeds in the millisecond range per frame to be viable in real-time seam-tracking, especially in high-throughput environments. Temporal consistency is vital to prevent frame-to-frame fluctuations in detected seam positions, which can result from noise, motion blur, or partial occlusions. To address this, temporal filtering techniques, such as Kalman filters or recurrent neural networks (RNNs), are integrated to smooth predictions and maintain tracking stability. Systems must also interpolate across brief losses of visual information due to occlusions from spatter or part geometry. Adaptability is both an advantage and a challenge for vision-based seam-tracking. The sensor system must handle joint transitions, surface finish variations, and illumination changes without manual recalibration. Techniques such as domain adaptation, online learning, and auto-tuning of detection thresholds are actively being developed to improve robustness in variable industrial environments. System calibration plays a crucial role in translating image coordinates into robot motion commands. Precise calibration of camera intrinsic and extrinsic parameters, sensor-laser offsets, and robot kinematic models is essential. Multi-camera setups or stereo vision systems, while offering improved depth perception and occlusion resilience, require more complex calibration procedures. In summary, the effectiveness of vision-based seam tracking relies on a harmonious integration of optical hardware, resilient image analysis algorithms and precise calibration with the welding robot as illustrated in Fig. 2. As vision systems continue to evolve with advancements in AI and edge computing, they are poised to further enhance the capabilities of high-speed, high-accuracy robotic laser welding.

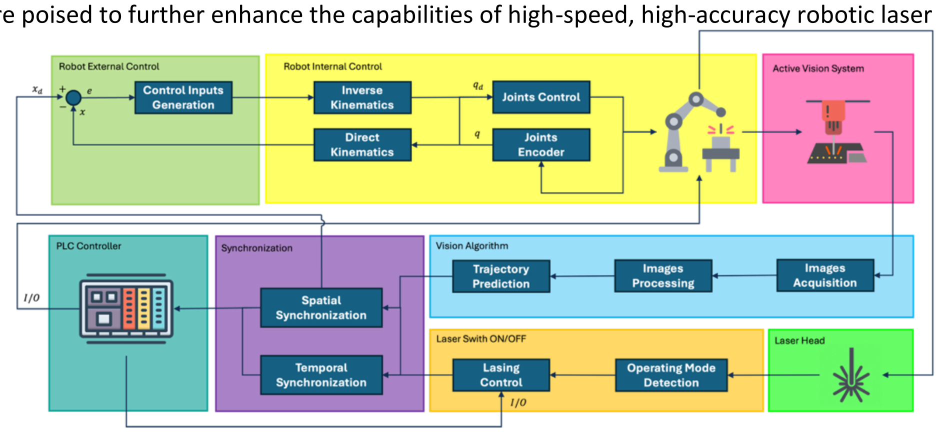


Fig. 2: Schematic overview of the vision-based seam tracking control system, highlighting the integration of image acquisition, real-time processing, and trajectory correction in coordination with the welding robot

3. Experimental Determination of Spatial and Temporal Seam-Tracking Requirements

To translate the theoretical framework of seam tracking requirements into quantifiable performance indicators, a series of experiments were conducted using an industrial robotic laser welding system equipped with a vision-based seam tracking solution. These tests were designed to validate key criteria defined in Section 2, such as spatial accuracy and processing latency under controlled but industrially relevant conditions. The aim was to evaluate how the sensor and the computational subsystems perform under varying geometric and environmental challenges and to assess the degree to which modern vision-based tracking systems can satisfy the stringent demands of robotic laser welding across different conditions and configurations.

3.1. Robotic laser welding cell

The experimental validation was carried out using a robotic laser welding system developed by BLM Group – Adige S.p.A. The system integrates a $6\ \mathrm{kW}$ fiber laser source (IPG Photonics YLS 6000) and a wobbler welding head (IPG Photonics D50), equipped with $300\ \mathrm{mm}$ focal and $200\ \mathrm{mm}$ collimation lenses to enable beam modulation for enhanced weld adaptability. The theoretical Rayleigh length of the optical setup was $1.5\ \mathrm{mm}$, resulting in a focused spot size of $150\ \mu\mathrm{m}$. The laser head was mounted on a 6-axis anthropomorphic robot (ABB IRB4600), offering precise and repeatable movement along complex trajectories. Workpiece positioning and angular manipulation were facilitated by an integrated tilting-rotary table (ABB IRBPA250), enabling multi-axis seam accessibility and stable clamping conditions. An overview of the robotic welding cell and a detailed image of the laser head assembly are illustrated in Fig. 3. To enable real-time seam-tracking, the system was equipped with a custom-designed coaxial vision-based monitoring apparatus, integrated directly onto the laser head. The imaging unit comprised a monochrome CMOS camera paired with an optical system optimized for grayscale imaging under active illumination at $660\ \mathrm{Nm}$. The configuration ensured high-contrast image acquisition of the seam's region with an optical resolution of $20\ \mu\mathrm{m/px}$, allowing the detection of fine details such as ideal $0\ \mathrm{mm}$ gap butt joints, which typically measure around $0.1\ \mathrm{mm}$. Optical filtering was employed to suppress near-infrared process emissions and laser back-reflections, minimizing the impact of spatter and plasma on imaging performance. This vision system was designed to maintain consistent image quality under varying welding conditions, supporting accurate seam detection even in the presence of surface reflections or moderate defocusing. Integration of the camera into the laser head allowed for coaxial alignment with the beam, simplifying calibration procedures.

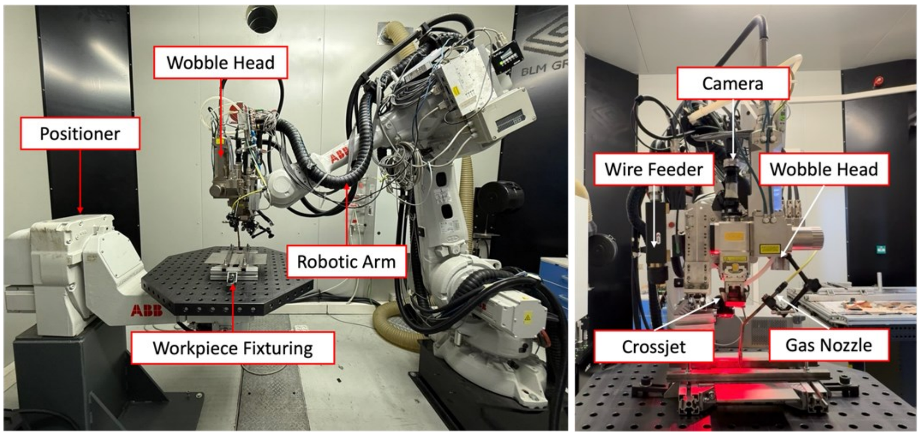


Fig. 3: (a) Robotic experimental welding cell; (b) The wobble laser welding head

3.2. Experimental Protocol and Beam-to-Seam Deviation Measurement Strategy

To evaluate the spatial tolerance of the seam-tracking system and validate its capability to maintain weld quality under misalignment conditions, a series of controlled lateral deviation tests were carried out. The purpose of these tests was to determine the maximum lateral deviation between the laser beam and the joint centerline that can be tolerated without compromising weld integrity. The test scenario was based on three millimeters thick AISI 301LN stainless steel sheets arranged in a butt joint configuration, prepared with nominal zero-gap conditions. Welding was performed without filler wire to ensure that the sensitivity to positioning errors was maximized. A schematic representation of the tests performed is provided in Fig. 4.

The test protocol involved introducing a precisely controlled lateral offset between the laser beam and the actual seam centerline. Offsets were incrementally increased from 250 µm to 500 µm, in steps of 50 µm. In parallel, different wobble amplitudes ranging from 0.5 mm to 2.0 mm were applied to assess their effect on the system's tolerance to misalignment. This allowed for a systematic investigation of the interaction between wobble amplitude and the maximum permissible beam-to-seam deviation, with the aim of identifying potential correlations. The selected offset values were based on the nominal spot size ($150\ \mu\mathrm{m}$), taking into account a defocus of $-2\ \mathrm{mm}$ that resulted in an effective beam diameter of $252\ \mu\mathrm{m}$. This configuration simulates realistic worst-case deviations that might occur due to tracking errors or calibration drift. To generate the deviations, the robot path was deliberately shifted perpendicular to the joint axis, while maintaining constant the process parameters as summarized in Table 1. Each test was replicated under identical conditions to ensure repeatability. Each weld was evaluated at its midpoint using metallographic cross-section analysis. Samples were prepared by standard grinding, polishing, and etching. The analysis aimed to assess the fusion penetration depth, the weld symmetry, seam alignment and the presence of defects such as lack of fusion or undercut. The key measurement metric was the effective beam-to-seam deviation, derived by fitting a circumscribed circle to the fusion zone in the cross-section and calculating the offset between the circle center and the nominal seam position. While this study focused on stainless steel butt joints, the same methodology is designed to be extensible to other materials and joint types (e.g., lap, fillet), enabling generalization of the derived spatial accuracy thresholds.

Table 1. Process parameters of the performed controlled lateral shift tests

Fixed Parameters	Value
Power $[\mathrm{kW}]$	2
Weld Speed $[\mathrm{mm/s}]$	25
Focal position $[\mathrm{mm}]$	-2
Beam size on the workpiece $[\mu\mathrm{m}]$	252
Wobble Frequency $[\mathrm{Hz}]$	50
Variable Parameters	**Value**
Wobble Amplitude $[\mathrm{mm}]$	0.5-2.0
Lateral Shift Deviation $[\mu\mathrm{m}]$	250-500

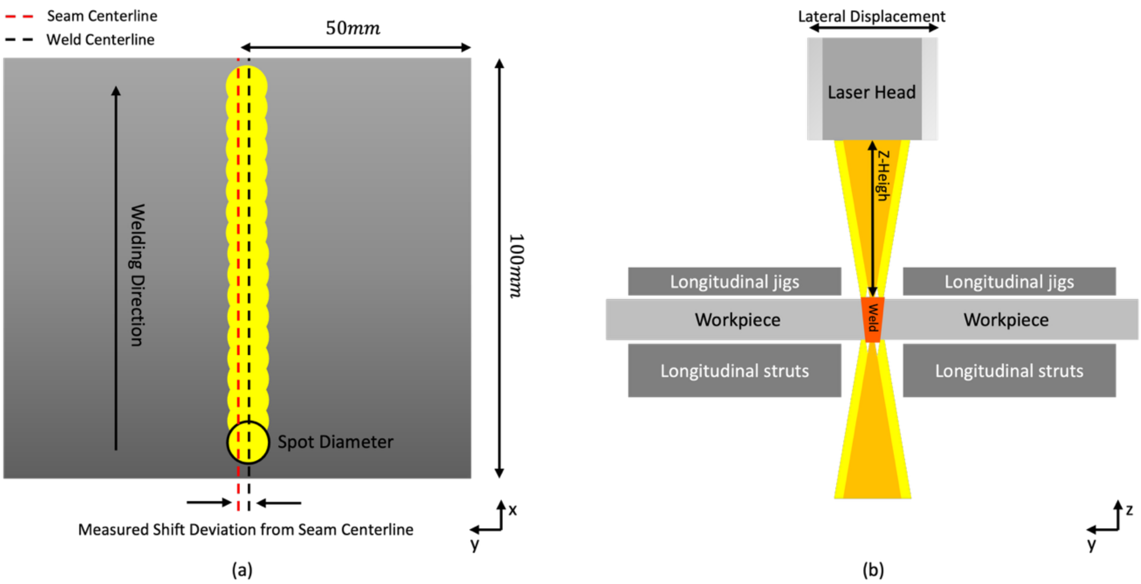


Fig. 4: Schematic representation of the lateral deviation test setup, shown in both top-down (a) and side (b) views.

3.3. Computational Requirements and Timing Constraints

To ensure real-time responsiveness of the seam-tracking system, a comprehensive timing analysis was carried out, encompassing the entire processing pipeline from image acquisition to actuation. The system's response time (t_{resp}), was decomposed into four key components: camera acquisition time (t_{cam}), algorithm inference time (t_{alg}), idle time or synchronization delay (t_{idl}), and actuation delay (t_{act}). Fig. 5 (a) illustrates the temporal sequence of three consecutive processing cycles, emphasizing the need for coordination within the camera frame rate (f_{cam}) and the control loop frequency (f_{ctrl}). The camera acquisition time (t_{cam}), as detailed in Fig. 5 (b), is composed of two fundamental sub-components: the exposure time (t_{exp}), which defines the duration during which the sensor integrates light to form an image and the readout time ($t_{readout}$), corresponding to the interval needed to transfer the acquired image from the sensor to the processing system. In this setup, exposure time was typically set to values between $200\ \mu s$ and $300\ \mu s$, depending on surface reflectivity and lighting conditions, while readout time was characterized at approximately $3-4$ ms. These values ensure that the camera operates comfortably at a high frame rate, avoiding frame drops or acquisition delays. Assuming, for example, that the camera system operates at a frame rate of 100 Hz, it is necessary to imply a maximum allowable image processing time of 10 ms to prevent backlog or delay propagation. The prediction algorithm, responsible for extracting seam position and gap features, was benchmarked with an average inference time of ≤ 10 ms, satisfying this constraint. This ensures that seam detection remains aligned with the camera's acquisition cycle. The actuation time (t_{act}) was estimated at 30 ms including a nominal $20\ ms$ communication delay and an additional $10\ ms$ for execution, in line with specifications from major industrial robot manufacturers.

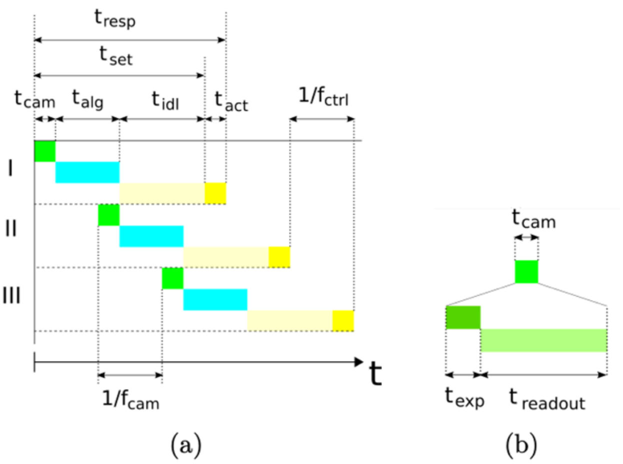


Fig. 5: (a) Temporal sequence of three consecutive processing cycles, highlighting the coordination required between the camera frame rate and the control loop frequency; (b) Breakdown of the camera acquisition time which includes the exposure time and the readout time.

4. Results

4.1. Correlation Between Wobble Amplitude and Maximum Admissible Beam Misalignment

The previously described tests were designed not only to define a spatial tolerance threshold for the seam-tracking system but also to investigate how beam wobbling influences the system's ability to compensate for lateral misalignments. The results demonstrate that the introduction of beam wobbling significantly affects the robustness of the welding process against positioning errors. As illustrated in Fig. 6, a clear linear correlation was observed between the wobble amplitude and the maximum admissible lateral deviation. Specifically, increasing the wobble amplitude from $0.5\ mm$ to $2.0\ mm$ led to a proportional increase in the system’s tolerance to beam-to-seam misalignment. This behavior is attributed to the broader effective interaction zone generated by larger wobble amplitudes, which helps maintain stable fusion even when the laser beam is not perfectly centered on the seam. Importantly, this curve allows us to identify two distinct regions: the area below the curve, which corresponds to combinations of wobble amplitude and lateral deviation that result in defect-free welds, and the area above the curve, where the process is no longer robust and welding defects are likely to occur. This graphical boundary thus provides a practical criterion for selecting safe operating conditions. These findings highlight the potential of integrating beam wobbling with vision-based seam tracking to enhance process robustness, particularly in applications involving narrow or geometrically variable joints, where tight spatial tolerances would otherwise limit welding stability.

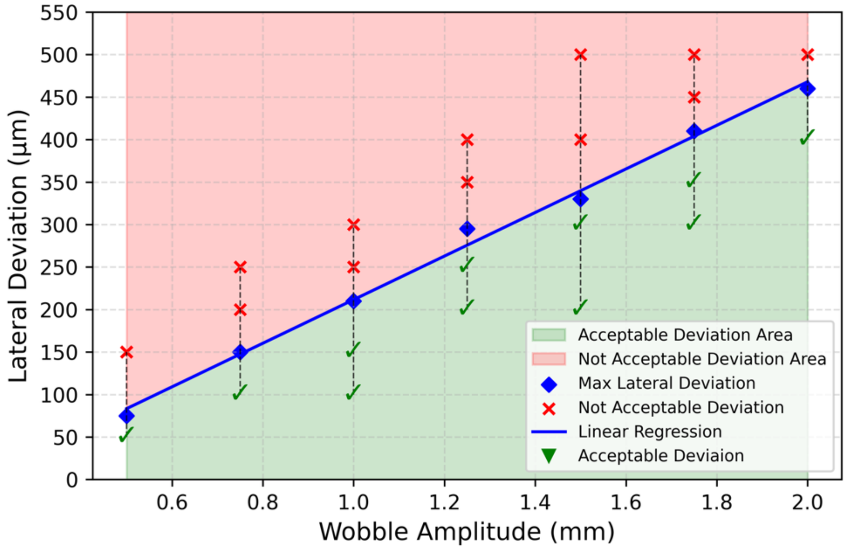


Fig. 6: Linear Correlation between Wobble Amplitude and Maximum Admissible Beam Misalignment

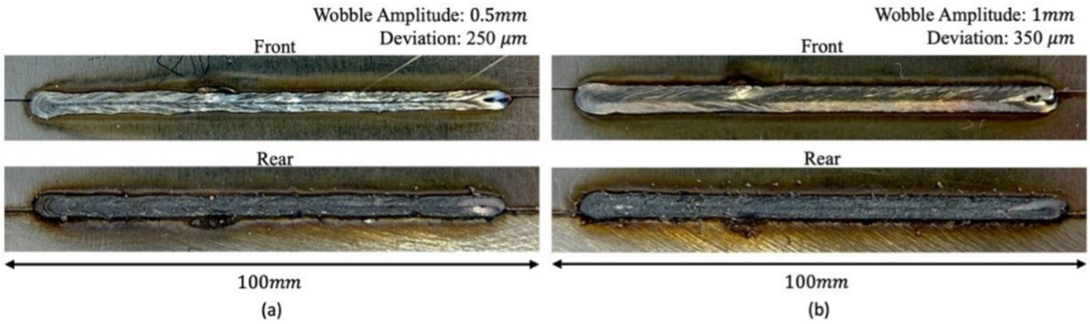


Fig. 7: (a) Misalignment weld result with a 0.5 mm wobble amplitude and 250μm lateral deviation; (b) Misalignment weld result with a 1 mm wobble amplitude and 350μm lateral deviation

Examples of the effects of beam-to-seam misalignment are illustrated in Fig. 7, which presents two representative test cases. In the first scenario, with a wobble amplitude of $0.5\ mm$ and a lateral deviation of $250\ \mu m$, and in the second, with a $1\ mm$ wobble amplitude and a $350\ \mu m$ deviation, welding defects were observed. These examples clearly demonstrate the impact of exceeding the admissible deviation threshold. To validate the observed correlation, metallographic cross-section analyses were performed on representative samples at the midpoint of each weld. The aim was to identify the maximum lateral deviation that still guarantees complete and defect-free joint fusion, using it as an empirical threshold for the spatial tolerance of the seam-tracking system under different wobble configurations. For instance, as highlighted in Fig. 8, corresponding to the cross sections of the welding configuration with a $1.5\ mm$ wobble amplitude, lateral deviations up to $300\ \mu m$ consistently resulted in high-quality welds with full penetration, symmetric fusion, and no observable defects. Exceeding this threshold led to the appearance of local lack of fusion and peripheral undercutting, indicating that the maximum admissible misalignment for maintaining weld integrity in this configuration is $\pm 300\ \mu m$. To quantify the actual beam deviations, the center of a fitted circle circumscribing the fusion zone was used as a proxy for the effective beam position. This was then compared to the nominal seam centerline to compute the true lateral error, which was validated against the programmed robot offset. The strong agreement between imposed and measured deviations confirms the consistency of the methodology and reinforces the defined thresholds as realistic spatial tolerance limits for the system. These results demonstrate that the integration of beam wobbling with advanced seam-tracking approaches, particularly those capable of estimating seam centerline and gap width, can significantly relax positioning accuracy constraints. Such strategies are especially promising for applications involving narrow or irregular joints, where tight spatial tolerances would otherwise limit process stability.

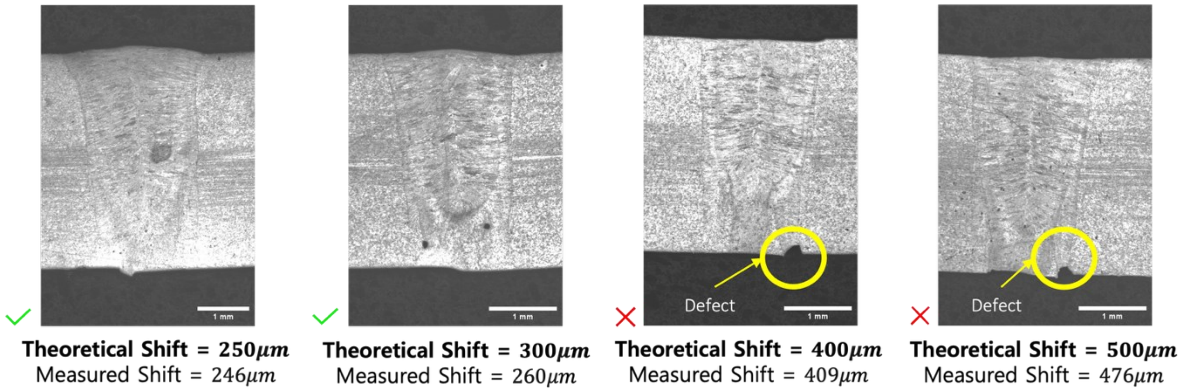


Fig. 8: Comparison between imposed lateral deviations and measured deviations obtained from cross sectional weld analysis

4.2. Response Time Characterization for Real-Time Operation

The total response time $(\mathrm{t_{resp}})$, which defines the required spatial distance, referred to as the forerun, between the current laser position and the point where corrections are applied, can be expressed as:

$$t_{resp} = \frac{forerun}{v_{weld}} \geq t_{cam} + t_{alg} + t_{act} \tag{1}$$

Given a maximum welding speed of $\mathrm{v_{weld}} = 100\,\mathrm{mm/s}$, the system requires a minimum forerun distance of $5\,\mathrm{mm}$. In practice, this was conservatively set to $6\,\mathrm{mm}$, allowing a safety margin to absorb occasional processing or communication delays. Importantly, this response time can be further optimized by spatial-temporal synchronization strategies. By leveraging overlapping image windows across successive frames and enforcing temporal consistency checks on seam position predictions, it is possible to reduce the number of processed images, the waiting and idle times and stabilize tracking without increasing latency. These techniques allow the system to make use of partially redundant spatial information and validate predictions over time, thereby improving both responsiveness and robustness. This analysis confirms that the proposed system architecture meets the real-time control constraints necessary for reliable closed-loop seam tracking at industrially relevant welding speeds and supports synchronized execution of control actions in high-throughput robotic welding operations.

5. Conclusion

This paper has presented a unified framework for defining and experimentally validating the core requirements of robust seam-tracking in robotic laser welding, with a specific focus on vision-based systems. Through a combination of theoretical analysis and experimental validation, this study identified key spatial, computational, and sensor-related factors affecting the precision and robustness of automated seam tracking under real-world manufacturing conditions. In detail, spatial domain experiments involving controlled beam-to-seam offsets revealed a linear relationship between the maximum permissible deviation and the beam's wobble amplitude. These findings highlight the potential of integrating adaptive beam shaping with advanced tracking strategies to reduce positional accuracy constraints while preserving weld quality. On the computational side, the timing analysis confirmed that the proposed architecture satisfies the real-time requirements of industrial robotic welding. The full processing pipeline, comprising image acquisition, prediction, and actuation remains within a sub-$50\,\mathrm{ms}$ window, enabling stable operation at speeds up to $100\,\mathrm{mm/s}$. The breakdown of acquisition timing into exposure and readout phases provided additional insight into camera performance, while spatial-temporal synchronization strategies were shown to further enhance tracking responsiveness and stability. Overall, the experimental setup and methodology presented provide a replicable and quantifiable basis for evaluating seam tracking technologies in laser welding. The results underscore the importance of aligning sensing precision with control responsiveness and demonstrate how the approaches involving vision-based control strategies can be leveraged to meet the evolving demands of high-throughput, high-precision manufacturing environments.

Beyond simple positional correction, modern seam-tracking systems are evolving into intelligent process control components. By dynamically adjusting laser parameters such as power, speed, or beam shaping in response to real-time seam data, they enable adaptive and optimized welding strategies. The integration of AI-assisted methods and sensor fusion is accelerating this transformation, allowing predictive adjustments and behavior adaptation based on historical and real-time data. Consequently, seam-tracking is transitioning from a reactive correction mechanism to a central pillar of next-generation robotic laser welding systems.

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