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Real-time laser weld point seam tracking system for robotic welding

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ABSTRACT

This paper presents a real-time vision-based laser weld seam tracking system optimized for robotic welding. The core innovation is a computer vision algorithm that processes video data to detect welding points with high precision, achieving an average absolute error of ±0.23 mm, with varying precision for different joint types (butt joint: ±0.63 mm, lap joint: ±0.04 mm, circular lap joint: ±0.02 mm). Integrated into an NVIDIA Jetson Nano, the system demonstrates robust real-time performance, processing video at 30 FPS for 720p resolution. By leveraging HSV color space analysis, morphological operations, and contour detection, the system effectively isolates and tracks laser points under dynamic conditions. Experimental results across butt, lap, and circular lap joints highlight its adaptability, with errors varying due to joint geometry and environmental factors. Comparative analysis shows superior accuracy over existing methods, such as a 0.31 mm error in laser-structured systems. By integrating directly with robotic welding tools, the system enables precise real-time adjustments, reducing human intervention and improving weld quality. This study provides a significant contribution to advancing automated welding technology.

Keywords: Robotics, seam tracking, laser welding, computer vision, real-time processing, jetson nano

INTRODUCTION

Laser welding is pivotal in modern manufacturing for its precision and efficiency. However, traditional systems often struggle to maintain accuracy under dynamic conditions, leading to inconsistencies in weld quality. To address these challenges, automated vision-based tracking systems have emerged as a promising solution, enabling real-time adjustments to enhance precision. This paper presents a novel system that integrates computer vision with robotic control, utilizing real-time image processing to accurately detect and track welding points, thereby improving the reliability and consistency of the welding process.

What sets laser welding apart is its ability to create deep and strong welds while keeping heat-affected areas to a minimum. This not only reduces distortion but also produces clean, high-quality joints, making it the go-to method for challenging applications (Sivasankaran, 2024). Its speed and seamless compatibility with automated systems make it an essential tool for improving production efficiency, significantly cutting down manufacturing times (Parchegani et al., 2023).

As the manufacturing world embraces digital transformation, laser welding is evolving with the integration of smart technologies. Real-time monitoring, powered by big data analytics, is reshaping how welding is done-optimizing processes, ensuring consistent quality, and reducing errors (Aminzadeh et al., 2023). Advanced monitoring tools now allow manufacturers to make on-the-spot adjustments, leading to superior quality control (Hsu & Salminen, 2023).

However, traditional manual and semi-automatic laser welding systems still face significant challenges. They often struggle to maintain precision in dynamic conditions, leading to inefficiencies and inconsistent results. For example, manual systems can falter when faced with sudden changes in welding paths, resulting in delays and inaccuracies (Li et al., 2022). Additionally, the variability of human operation often leads to uneven weld quality, particularly in unpredictable environments (Yu et al., 2022). These challenges, combined with the need for skilled operators, drive up costs and make scaling difficult (Yu et al., 2022).

To overcome these issues, robotic welding systems are stepping in with innovative solutions. These systems excel at adapting to variations in material shapes and environmental conditions, ensuring consistent weld quality. Real-time processing enables robots to adjust their paths dynamically, even in complex scenarios. Automated joint detection systems further boost efficiency by precisely guiding robotic arms to welding points, addressing labor shortages and enhancing productivity (Kos et al., 2019; Lee et al., 2024).

Recent advancements in deep learning have taken robotic applications to the next level (Karadeniz et al., 2024; Karadeniz & Koçak, 2024). In the study conducted in the Visual Studio Code program, the laser point was detected with an absolute error of 0.8 mm (Kocak & Saygın, 2024). The integration of laser-structured light has significantly improved welding

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accuracy, reducing errors to as low as 0.31 mm (Nguyen et al., 2024). Deep learning-based key point detection models now achieve over 80% accuracy even in complex environments (Mobaraki et al., 2024). Building on these advancements, our approach further improves welding accuracy by achieving an average absolute error of 0.23 mm, surpassing some conventional techniques while maintaining real-time processing capabilities. Algorithms such as YOLO, used for detecting welding paths, have reached near-perfect precision rates of 99.5% (Reddy et al., 2024). These breakthroughs are redefining robotic welding and setting new benchmarks for accuracy and adaptability in manufacturing environments (Umar et al., 2025).

This paper introduces an advanced system for detecting laser points during welding for various joint types, such as butt joints, lap joints, and circular lap joints, illustrated in **Figure 1**. Using computer vision techniques, the system identifies the laser's position in video data through HSV color space analysis. Noise is reduced with morphological operations like erosion and dilation, while smooth tracking is achieved by minimizing abrupt positional shifts. Built on the NVIDIA Jetson Nano platform, the system processes data quickly and accurately transmits laser coordinates to robotic welding systems. This integration enables precise torch control, reduces human intervention, and lays the groundwork for fully automated welding solutions.

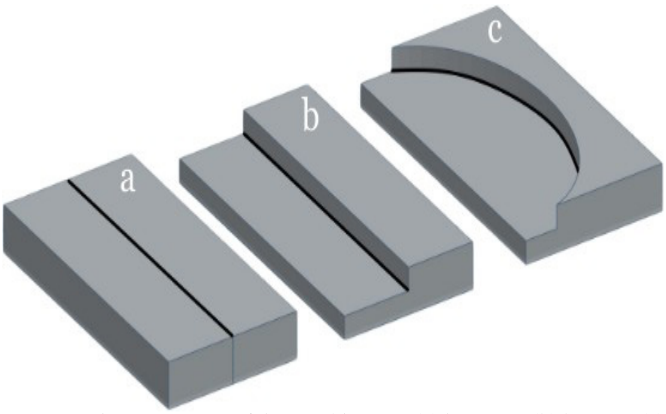

Figure 1. The comparison of three weld pieces: (a) butt joint (b) lap joint (c) circular lap joint

The proposed system has been rigorously tested and has shown significant improvements in both reliability and precision. By combining advanced detection algorithms and real-time processing, it ensures dependable performance, making it highly suitable for industrial use. These improvements streamline the welding process, reduce errors, and represent a significant step forward in automated welding technology.

This paper is organized as follows: The first section explains the algorithm development process, detailing steps like converting frames to HSV color space, reducing noise with Median Blur, creating masks, and detecting contours to locate the laser's source point. The second section focuses on real-time integration and testing, including video frame processing, tracking the laser smoothly, and overcoming challenges during implementation. Finally, the results and discussion section evaluate the system's performance in terms of accuracy and efficiency, explores noise management, and highlights potential improvements and broader applications.

METHODOLOGY

In this paper, laser light is projected to the point to be welded, and the point where the laser light is refracted is determined as the welding point. This process involves the real-time detection of source points from video images and the calculation of their coordinates. The analyses and the theoretical foundations applied in the related image processing techniques and mathematical approaches are detailed below.

Laser Light Properties and Detection

The unique properties of laser light, combined with the effectiveness of the HSV color space, have been extensively explored, particularly under varying lighting conditions. Studies highlight the benefits of the HSV model, which separates color information (hue) from intensity (value), thereby enhancing detection accuracy in challenging environments.

The HSV color space has proven effective for filtering fire-like colors, significantly improving detection in vision-based systems (Muhammad et al., 2023). Adaptive thresholding techniques, when combined with morphological processing, have shown that the HSV model is highly effective in detecting objects under dynamically changing lighting conditions (Zhao et al., 2013). Moreover, advanced approaches like QRCP decomposition applied in the HSV color space have improved image processing in low-light environments, leading to enhanced visibility and contrast, which are critical for accurate detection (Ye et al., 2023). The unique characteristics of laser light, including its high brightness and distinct color, make it easily distinguishable from other light sources. This paper utilizes the HSV color space to isolate laser light effectively, with the HSV range for red laser light defined as [172, 175, 175] to [180, 255, 255]. This configuration ensures robust detection across various lighting conditions and backgrounds.

Video Input and Color Conversion

One essential step in detecting laser light involves converting video frames from the RGB color space to HSV using OpenCV. The ability of the HSV model to separate brightness (value) from color (hue and saturation) makes it particularly effective in environments with variable lighting. This advantage has been documented in numerous studies focusing on object tracking and color recognition (Zhao et al., 2013; Cai et al., 2012).

OpenCV provides efficient tools for HSV processing, enabling real-time object tracking with accuracy rates reportedly reaching up to 90% (Gulzar et al., 2022). By applying specific thresholds to the hue channel of HSV-converted video frames, red laser light can be effectively isolated. This method has proven highly beneficial in applications like surveillance and object tracking, where it minimizes noise and enhances detection performance (Gogi & Uttarakumari, 2017).

The video was recorded using an industrial-grade Basler Ace 2 camera at a resolution of 720p and 30 FPS. Each frame, represented as $V = \{v_i \mid i \in N\}$, was first captured in the BGR color space and then converted to HSV using OpenCV's cv2.cvtColor function. A 650 nm red diode laser with a 5 mW power output was used, ensuring consistent visibility across different workpiece surfaces. The pixel values were then processed as shown in equation (1).

$$f(R, G, B) = (H, S, V) \quad (1)$$

This transformation enabled the application of predefined HSV thresholds for isolating red tones, ensuring accurate detection of the laser light in each frame.

Noise Reduction and Masking

To address speckle noise and specular reflections, which are common in welding environments, the system employed a combination of Median Blur and adaptive thresholding. Median Blur is particularly effective at reducing salt-and-pepper noise while preserving edges, which is crucial for applications involving laser detection (Draz et al., 2023).

Recent advancements in noise reduction, including structure-oriented and space-varying median filtering, have further enhanced accuracy by focusing on specific regions of noise corruption (Oboué et al., 2024). These methods have demonstrated significant improvements in signal-to-noise ratios for real-time systems, including laser detection applications (Kumar et al., 2023).

In this paper, a Median Blur filter was applied to each frame, denoted as M (vi), as presented in equation (2).

$$M(v_i) = \text{median\_blur}\,[HSV(v_i), k = 5] \tag{2}$$

After applying Median Blur, a bilateral filter was selectively used to preserve edges while reducing high-frequency noise. This dual approach effectively mitigated artifacts caused by spatter and reflections. Subsequently, a binary mask L(vi) was created using OpenCV's cv2.inRange function, which isolates pixels within the defined HSV range for red laser light, as presented in Equation (3).

$$\mathbf{L(v_i)} = \begin{cases} \mathbf{1} & \textbf{if } [172,175,175] \le (\mathbf{H,S,V}) \le [180,255,255] \\ \mathbf{0} & \textbf{otherwise} \end{cases} \tag{3}$$

Morphological operations, including erosion and dilation, were subsequently applied to refine the mask. While erosion eliminates small artifacts, dilation emphasizes the laser light, enhancing its visibility against the background.

Contour Detection and Determination of Source Points

Contour analysis is a critical step for accurately tracking and detecting laser light. By applying contour extraction algorithms, laser systems can effectively determine the shape and position of detected objects (An et al., 2019). These techniques are particularly valuable in industrial applications such as laser cutting and welding, where precision is paramount (Franz et al., 2011).

Contours were extracted from the binary mask using OpenCV's cv2.findContours function. Among the identified contours {C1, C2, … , Cn}, the largest contour C_{max} was selected based on area, as presented in equation (4).

$$C_{max} = \max\,[\{\text{area}\,(C_i) \mid i \in \{1, \dots, N\}\}] \tag{4}$$

The source point of the laser, (cx, cy), was determined as the leftmost point within C_{max}, as presented in equation (5).

$$c_x = \min\,[\{x_j \mid (x_j, y_j) \in C_{max}\}],\ c_y = \text{corresponding } y \tag{5}$$

To ensure smooth tracking, the distance d between consecutive source points was calculated, as presented in equation (6).

$$\mathbf{d} = \sqrt{(\mathbf{c_x} - \mathbf{c_{x_{previous}}})^2 + (\mathbf{c_y} - \mathbf{c_{y_{previous}}})^2} \tag{6}$$

If d exceeded a predefined threshold of 75 pixels, the current point was reset to the previous point, preventing abrupt shifts and ensuring smoother tracking.

Visualization and Display

Real-time visualization of laser tracking is essential for various applications, from alignment tasks to UAV target tracking. OpenCV has emerged as a key tool, supporting advanced tracking systems with its comprehensive library of algorithms and deep learning integration (Yang, 2023).

Recent innovations, such as parallel multi-target detection algorithms, have improved accuracy and efficiency, achieving detection rates of up to 90% in complex environments (Cao et al., 2023). In robotic and UAV applications, laser spot detection systems have demonstrated low error rates and high execution speeds, significantly advancing practical use cases (García-Cardenas et al., 2020).

In this work, each frame's detected laser position (cx, cy) was highlighted using OpenCV's cv2.circle function for real-time visualization. Both the binary mask and the processed frame were displayed with cv2.imshow, allowing precise tracking of the laser's movement across frames.

EXPERIMENTAL STEPS

The experimental procedure in this paper comprises several stages of image processing, including identifying laser tracking points, extracting their coordinates, and marking these coordinates for visualization. The algorithm is then implemented in real-time on the NVIDIA Jetson Nano developer kit. Video input was captured using an industrial-grade Basler Ace 2 camera operating at 720p resolution (1280×720 pixels) and 30 frames per second (FPS), ensuring high-quality data acquisition under dynamic welding conditions. The camera was mounted 30 cm above the workpiece with a fixed focal length to ensure consistent imaging. A 650 nm red diode laser with a 5 mW output power was utilized to project the welding points. To optimize the reflection visibility, the laser was reflected at a 30° angle.

The initial stage involves identifying laser tracking points using computer vision techniques. Video frames are converted from the RGB color space to HSV to effectively isolate the red laser light, a process that leverages the HSV model's ability to separate brightness from color. This conversion proved particularly beneficial in environments with variable lighting, such as industrial settings with intermittent arc glare. To enhance the precision of laser detection, noise reduction techniques such as median Blur (kernel size=5) were applied. This technique effectively reduces salt-and-pepper noise while preserving edges, crucial for maintaining the integrity of laser point detection. After noise reduction, a binary mask was created to isolate pixels within the defined HSV range for red laser light (H: 172-180, S: 175-255, V: 175-255). Morphological operations, including erosion (3×3 kernel) and dilation (5×5 kernel), were then applied to refine this mask, eliminating spurious artifacts caused by welding spatter.

The next stage involves contour analysis, a critical step for accurately tracking and detecting laser light. Contour extraction algorithms were applied to the binary mask to determine the shape and position of detected objects effectively.

Experiments were conducted on three joint types-butt, lap, and circular lap joints-using 5 mm thick ST37 steel plates, with 15 samples per joint type tested under controlled conditions. The largest contour was selected based on area, and the source point of the laser was determined as the leftmost point within this contour. The distance between consecutive source points was calculated to ensure smooth tracking, with a threshold of 75 pixels applied to suppress abrupt positional shifts caused by transient noise.

In the final stage, real-time visualization of laser tracking was performed on the NVIDIA Jetson Nano developer kit. The detected weld point in each frame was highlighted, and the x, y coordinates of the welding location were determined. Both the binary mask and the processed frame were displayed, enabling precise tracking of the weld location across frames. The experimental steps followed in this study are illustrated in **Figure 2**.

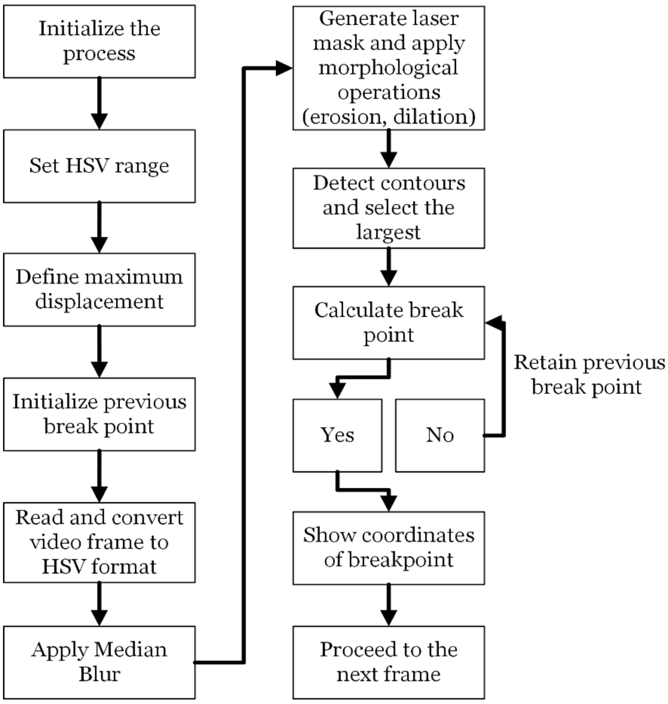

Figure 2. Flow diagram of the experimental steps

RESULTS

Through real-time video processing, the algorithm effectively isolated the laser light in complex and dynamic environments by leveraging the HSV color space and advanced noise reduction techniques. Contour analysis and morphological operations enhanced detection robustness, ensuring the laser points were accurately identified and smoothly tracked.

The proposed algorithm for detecting and tracking laser welding points using computer vision was successfully implemented and tested on the NVIDIA Jetson Nano in real-time applications. The system demonstrated high reliability, with impressive accuracy in determining laser source points. As shown in **Table**, the absolute errors varied across different joint types: a ±0.63 mm error was observed in the butt joint, ±0.04 mm in the lap joint, and ±0.02 mm in the circular lap joint. The average absolute error was calculated to be ±0.23 mm, reflecting the system's overall precision.

Table. Comparison of the models

Joint type	Average absolute error (mm)	Key observations
Butt joint	±0.63	A smaller refraction angle leads to higher error rates
Lap joint	±0.04	An overlapping structure increases the refraction angle
Circular lap joint	±0.02	A broader reflection area allows for clearer identification of the refraction point
Average	±0.23	Lap and circular lap joints exhibit significantly lower errors due to clearer reflections

In butt joints, where the two pieces are adjacent to each other, the refraction angle of the laser light is smaller, causing the laser light to scatter over a narrower area. In contrast, lap and circular lap joints, where the pieces overlap, result in a larger refraction angle, allowing for a broader reflection area and clearer identification of the laser dot. As a result, fewer errors are observed in lap and circular lap joints, while the error rate is higher in butt joints.

The seamless integration of this system with robotic welding tools enabled precise communication of welding coordinates, allowing for automated control of the welding torch. This advancement not only improved operational precision but also reduced the need for manual intervention, paving the way for more efficient and consistent welding processes.

As shown in **Figures 3-5**, the system successfully pinpointed laser locations in real-time scenarios, demonstrating its potential to enhance robotic welding technologies. In Figures 3-5, results belong to three different samples and are labeled as "a", "b", and "c".

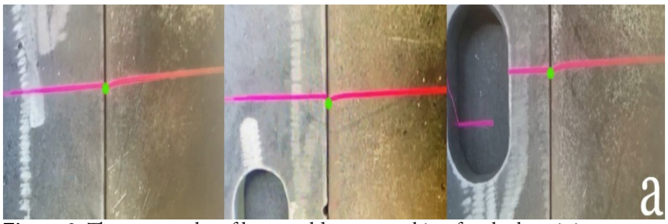

Figure 3. The test results of laser weld seam tracking for the butt joint

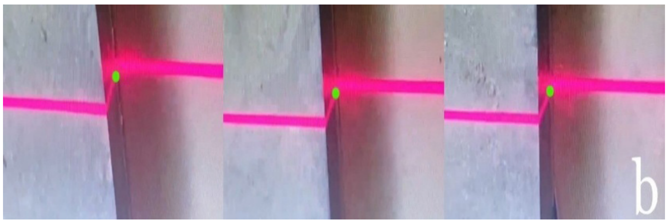

Figure 4. The test results of laser weld seam tracking for the lap joint

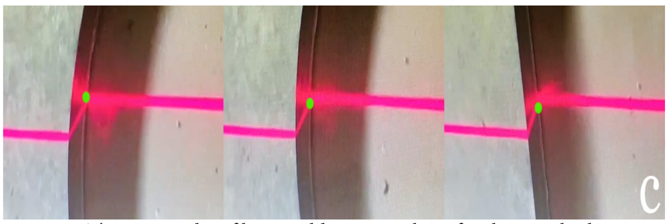

Figure 5. The test results of laser weld seam tracking for the circular lap joint

Future Work

The results of this research underscore the potential of this system to drive advances in automated welding technology with the flexibility to adapt to various industrial applications. Looking ahead, the approach will be expanded to cover a broader range of welding types, including MIG/MAG, TIG and laser spot welding, as well as applied to different types of welding parts. Although these achievements are promising, challenges remain, particularly in ensuring the system's reliability under a variety of environmental conditions and expanding its use in more complex welding scenarios. Overcoming these hurdles will be key to enabling wider adoption and further development. Furthermore, autonomous welding can be achieved by identifying the X and Y coordinates of the welding point and communicating them to the robot. The accuracy of this process can be enhanced using adaptive filtering techniques alongside customized methods for representing the robot's environment, specifically designed for its limited-scale visual perception (Karadeniz et al., 2021).

Future efforts will focus on improving the algorithm's adaptability to a range of welding conditions, including different materials and joint geometries. We also plan to explore the use of advanced machine learning techniques, such as deep learning, to enhance feature detection and prediction accuracy, as well as investigate deep learning-based enhancements to further improve tracking robustness under varying operational constraints. Additionally, testing the system in large-scale industrial settings and exploring its compatibility with other robotic systems will be critical for delivering more comprehensive automated solutions in manufacturing. By addressing these challenges and refining the integration of adaptive control strategies, this research aims to contribute to the next generation of intelligent and efficient robotic welding technologies. The combination of these advancements will not only bolster precision but also strengthen the system's real-time performance, paving the way for broader adoption in high-demand industrial environments (Cao et al., 2023).

CONCLUSION

This paper introduces a powerful, computer vision-based algorithm designed to detect and track laser welding points in real time, all integrated into an NVIDIA Jetson Nano platform. The system has shown exceptional accuracy, with a minimal error of just 0.23 in pinpointing the laser source points. By using the HSV color space and advanced image processing techniques, like morphological operations and contour analysis, the algorithm successfully isolates and tracks laser points in dynamic, real-world environments. The seamless integration with robotic welding tools allows for precise control of welding torches, minimizing manual intervention and significantly improving the efficiency and consistency of the welding process.

ETHICAL DECLARATIONS

Referee Evaluation Process

Externally peer-reviewed.

Conflict of Interest Statement

The authors have no conflicts of interest to declare.

Financial Disclosure

The authors declared that this study has received no financial support.

Author Contributions

All of the authors declare that they have all participated in the design, execution, and analysis of the paper, and that they have approved the final version.

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