AI-Driven Collaborative Welding: Innovations in System Setup and Intelligent Manufacturing

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***Abstract*—This paper proposes a new system model and setup for collaborative and AI-driven welding, designed to enhance precision, adaptability, and efficiency. By integrating advanced computer vision, real-time robotic control, and dynamic parameter adjustments, the system addresses key challenges in modern welding processes, including defect detection, process optimization, and seamless integration into diverse manufacturing environments. The system also enhances safety by minimizing human exposure to hazardous conditions and ensures consistent weld quality through real-time monitoring and feedback loops. Central to this innovation is a groundbreaking data acquisition process that not only accelerates decision-making but also drives the system's AI capabilities to new heights of accuracy and adaptability. This innovative setup highlights the transformative potential of intelligent welding systems, offering a pathway to improved flexibility, cost efficiency, and sustainability in modern manufacturing.**

***Index Terms*—Collaborative Welding, Artificial Intelligence, Intelligent Manufacturing, Robotic Control**

I. Introduction

Welding plays a crucial role in the manufacturing industry, and its significance has grown with the adoption of advanced technologies [1]. Traditional manual welding, which often relied on handheld tools, has gradually been replaced by automated systems powered by industrial robots [2]. While robotic welding has been established for decades, these systems were once limited to pre-programmed tasks with minimal adaptability. However, as welding processes become more complex and involve multiple parameters, there is an increasing demand for systems that can dynamically adjust to diverse tasks [2], [3]. Additionally, evolving production environments and specific customer requirements necessitate more flexible and efficient solutions. This has led to the development of next-generation welding systems capable of intelligent adjustments, ensuring high-quality output in customized production environments [4].

In recent years, welding technology has advanced significantly, driven largely by automation that has enhanced both process efficiency and quality [2]. The integration of Artificial Intelligence (AI) technologies, such as machine learning and deep learning, has revolutionized the field by enabling real-time monitoring and defect detection. AI has shown exceptional potential in predicting weld quality [5] and identifying defects [6], [7]. For example, [5] presented a novel approach to predict joint strength in ultrasonic welded thermoplastic composites using various neural networks. Moreover, the authors in [6] demonstrated the use of neural networks to predict welding defects with high accuracy, while [7] proposed a transfer learning-based solution using convolutional neural networks (CNNs) to achieve similar results.

The convergence of AI and Internet of Things (IoT) technologies has further enabled real-time process monitoring and control [8]. One significant application is predictive maintenance, where machine learning models analyze sensor data to predict potential equipment failures, thereby minimizing downtime and extending the lifespan of welding machinery [9]. Collaborative robots (cobots) also play an essential role in advancing welding operations. These robots, capable of working alongside human welders, adapt to complex welding tasks, improving flexibility, precision, and overall efficiency [11]. By leveraging AI, cobots not only assist human operators but also contribute to more intelligent and automated welding processes, ultimately enhancing quality and efficiency in modern welding environments [12].

In this paper, we explore the integration of cobots and AI in welding systems, emphasizing their potential to revolutionize modern manufacturing. This work investigates the challenges and advancements in implementing intelligent welding technologies, demonstrating the feasibility and benefits of adaptive, high-precision welding processes. Furthermore, we propose a novel system model that leverages real-time data acquisition, advanced computer vision, and dynamic parameter adjustments to optimize welding precision and efficiency. A significant aspect of this work is the development of an innovative data acquisition strategy, ensuring the collection of high-quality data necessary for training and refining the AI models, thus enabling superior system performance and scalability. This new model addresses limitations in traditional systems, offering enhanced adaptability, reduced operator workload, and improved resource utilization, making it a transformative approach for next-generation manufacturing environments.

II. Background & System Model

A. Collaborative Robots in Welding Industry

Cobots have emerged as transformative tools in the welding industry, offering enhanced flexibility, precision, and safety [12]. Unlike traditional industrial robots that require strict separation from human operators, cobots are designed to work alongside humans, enabling seamless collaboration and increased productivity. Their ability to adapt to dynamic production environments makes them especially valuable in modern manufacturing settings [13].

Cobots are widely used for tasks such as precision welding, adaptive welding, and operations in hazardous environments [14]–[16]. For example, cobots equipped with advanced sensors and vision systems can identify weld locations with high accuracy, ensuring consistent quality across repetitive tasks [15]. In hazardous conditions, cobots reduce human exposure to risks such as toxic fumes or high temperatures by performing dangerous welding tasks autonomously [16]. Additionally, their ease of programming allows for quick adaptation to new production requirements, as demonstrated in flexible manufacturing lines [17].

The integration of cobots in welding processes has resulted in numerous benefits, including improved safety, reduced setup times, and enhanced weld quality [15]. Cobots also contribute to cost savings by minimizing waste and optimizing resource utilization [18]. As advancements in AI and sensor technologies continue, the capabilities of cobots are expected to expand, further solidifying their role in smart manufacturing environments [13]. With these advancements, cobots will play a critical role in meeting the demands of highly customized and efficient production systems.

B. System Model

The proposed system leverages advanced computer vision, real-time robotic control, and automatic parameter adjustment to deliver highly precise and adaptable welding processes. The system consists of multiple interconnected components, as illustrated in Fig. 1, to ensure a seamless workflow and efficient performance.

1) Data Acquisition with High-Resolution Camera: The first step in the process involves the use of a high-resolution (3D) camera, which captures real-time images of the workpiece, particularly focusing on grooves. The camera feed is then sent to the AI processing unit, as shown in Fig. 1, where computer vision algorithms are applied to detect groove dimensions, positions, and orientations. This eliminates the need for manual marking and simplifies setup, while also reducing costs associated with specialized welding devices.

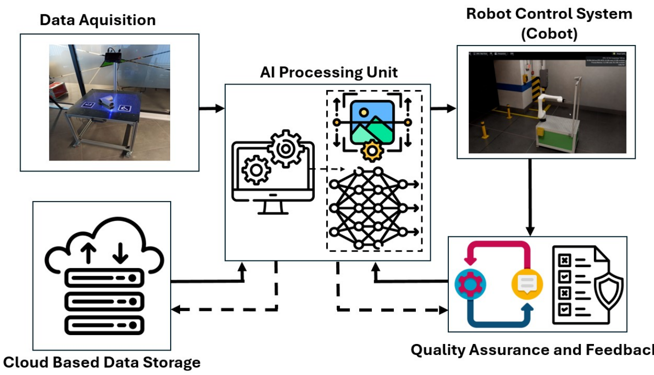

Fig. 1. System model diagram for intelligent welding: Integration of computer vision and real-time robotic control

Further details about the data acquisition process will be provided in Section III.

2) AI Processing Unit (Data Analysis and Control): The AI processing unit is responsible for processing the camera feed using sophisticated computer vision algorithms to extract crucial groove coordinates. Once the grooves are identified, the AI analyzes the data and makes decisions about the welding process. It also generates commands for the robot control system to guide the Cobot's movements (Fig. 1) and adjust welding parameters dynamically. Additionally, the AI processing unit dynamically adjusts welding parameters such as the welding gun distance, feed rate, voltage, current, and gas flow, optimizing these parameters based on real-time feedback to ensure optimal welding conditions.

3) Robot Control System (Path Tracking and Parameter Adjustment): The robot control system receives guidance from the AI processing unit, which sends real-time control commands based on the detected groove coordinates. The Cobot follows these instructions and performs the welding operation. Cobots are designed to work safely alongside human operators, adjusting their movements in real time based on AI-driven insights and compensating for any deviations from the intended trajectory.

A key feature of the system is the synergy between visual recognition and robotic control. The seamless integration of these two subsystems creates a strong synergistic effect, enabling extremely precise and consistent welding. The system combines the capabilities of the camera and robotic control to minimize preparation time and reduce potential errors, ultimately improving efficiency and adaptability to various welding tasks.

4) Continuous Feedback and Quality Assurance: After the welding process, quality assurance systems (e.g., high-resolution cameras and additional sensors) evaluate the weld quality, as depicted in Fig. 1. The feedback from these systems is sent back to the AI processing unit. The AI uses this feedback to refine its models and improve future welding tasks. This feedback loop creates a continuous learning process, enhancing the system's adaptability and overall performance over time.

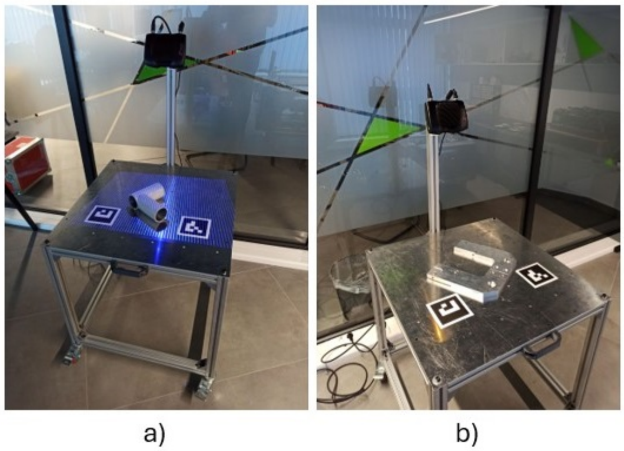

Fig. 2. Dataset generation setting in different situations and relationships: a) Plastic pipes joint capturing; b) Metallic L-profiles joint capturing.

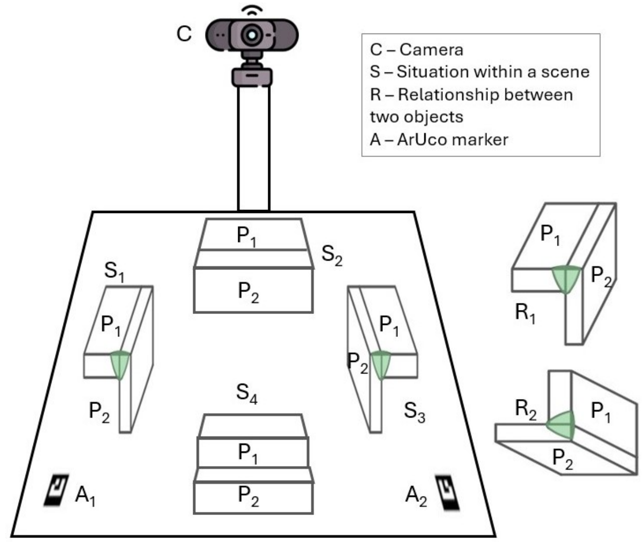

Fig. 3. Diagram of the visual environment.

5) Data Storage and Continuous Learning: Data collected from the system, including welding parameters, groove coordinates, and weld quality assessments, is stored in a cloud-based system. The AI processing unit accesses this data for long-term analysis and model retraining. This allows the system to learn from past operations and adapt to new welding tasks, materials, and conditions, ensuring continuous improvement in its performance.

III. Dataset Acquisition

The dataset was developed to support the creation of AI-driven algorithms for robotic welding applications. It incorporates diverse types of data to ensure comprehensive analysis and robust model development.

A. Workspace and Equipment Setup

During the dataset recording, a workspace with defined dimensions and a specific background color was prepared, as shown in Fig. 2, on which welding objects were placed. This setup ensures controlled and consistent data collection for the AI-driven algorithms in robotic welding. The Zivid 2+ (model M60) camera was used for data collection, and its placement and functionality were critical for capturing the necessary data. The camera was positioned above the workspace at a specific height and angle to capture accurate images and 3D data. It operates in three modes: 2D, 3D, and a combination of both, each serving a distinct purpose In 2D mode, the camera captures color images, while in 3D mode, it captures the point cloud data, depth maps, SNR maps, and normal maps.

Fig. 3 shows a sketch of the data collection setup, with simplified object shapes P1 and P2, providing a visual representation of how the objects were arranged during the data capture. In addition to point clouds, the camera generates additional data types, such as the color image, depth map, SNR map, and normal map, each contributing to the overall analysis of the scene. The imaging process can be performed in two ways: manual and automatic. In the automatic mode, the camera analyzes the scene, automatically adjusts various parameters, and then captures the image. In manual mode, users can adjust several parameters, including RGB and gamma values, image processing filters, and scene parameter settings to customize the data capture for specific needs.

B. Object and Scene Details

The objects used in the dataset, labeled as P1 and P2 (Fig. 3), were created as Computer–Aided Design (CAD) models to provide a precise representation of their geometry and relationships. These models were used both individually and as a combination (P1 ∪ P2) to simulate various welding scenarios. The relationship between the two objects, defined as R in Fig. 3, represents their relative position on the workspace. Specifically, the objects were manually placed in a way that their edges aligned, simulating a connection intended for welding. This setup allowed for a realistic simulation of welding tasks.

The dataset also includes different situations (S in Fig. 3) that represent various positions of the two objects within the same relationship in the scene. These variations in the placement of objects on the workspace simulate several real-world conditions. The situations include cases such as when the weld line is occluded (S4 in Fig. 3), fully visible (Fig. 3, S2), or partially visible (S1 and S3 in Fig. 3), providing a variety of challenges that an AI-driven algorithm for robotic welding might encounter. The position of the connected objects relative to the ArUco markers is also considered, helping to determine the approximate alignment and placement of the objects during the recording.

ArUco markers were placed on the workspace as part of the setup. These synthetic square markers feature a wide black border and an inner binary matrix that encodes their unique identifier (ID) (see Fig. 2). The black border helps facilitate rapid detection in the images, while the binary encoding

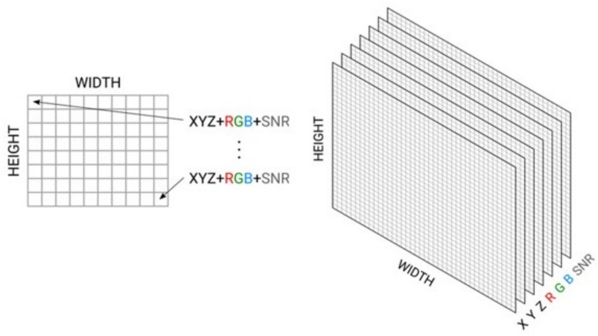

Fig. 4. Point cloud representation [20].

supports both identification and error detection/correction, ensuring accuracy in the data capture process.

C. Camera Positioning

The positioning of the Zivid 2+ M60 camera was adjusted during the dataset recording to ensure a thorough coverage of the workspace. The camera, which supports a working distance range from 300 mm to 1100 mm, was placed at two distinct working distances: 550 mm and 900 mm. These positions were chosen to provide different perspectives of the objects on the workspace, allowing for a range of data to be captured, from close-up details to broader coverage. This variation in camera positions helps simulate different angles and distances that the robotic welding system may encounter in real-world applications.

D. Point Cloud Data and Imaging Components

Point cloud [19] data plays a crucial role by providing a detailed 3D representation of the scene, as depicted in Fig. 4 [20]. It captures the spatial coordinates of every point in the field of view, enabling accurate reconstruction of the geometry and structure of objects within the workspace.

RGB images (Fig. 5 a)) offer complementary color information, allowing the dataset to integrate visual details with spatial data. This is particularly useful for tasks such as texture mapping and object recognition.

Depth maps, shown in Fig. 5 b), measure the distance between the camera and objects, providing essential data for precise measurement of object positions, which is key for applications like robotic navigation and depth-based segmentation.

SNR (signal-to-noise ratio) maps, depicted in Fig. 5 c), offer a measure of the reliability and quality of the captured data. These maps help identify regions with potential inaccuracies, which is crucial for ensuring the robustness and precision of AI models.

Normal maps (Fig. 5 d)) provide valuable information on surface orientations by defining the vector direction perpendicular to each point on an object's surface. This data is essential for understanding surface textures, gradients, and contours, which are important for welding tasks that require precise control over tool paths and interactions with the workpiece.

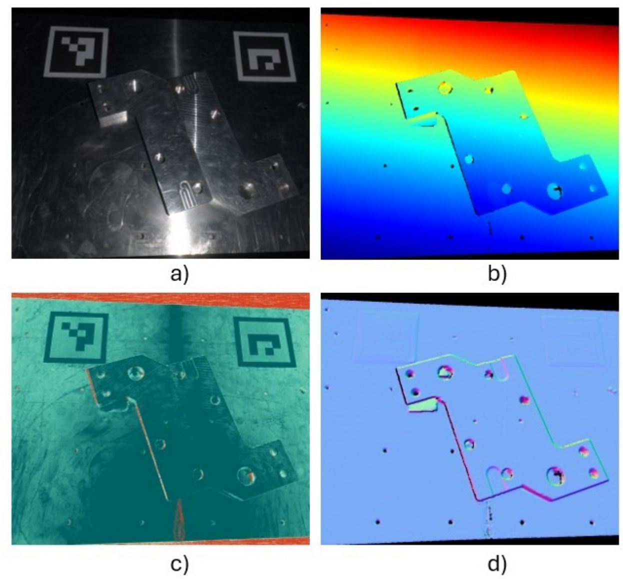

Fig. 5. Capture outputs: a) RGB image; b) Depth image; c) SNR image; d) Normal image.

Each point cloud within the dataset consists of approximately 5 million points, offering a high-resolution spatial representation of the scene. The dataset maintains a 1:1 pixel-to-point correlation, ensuring that every pixel in the captured image corresponds directly to a point in the 3D space. For each point, the dataset provides XYZ coordinates for spatial positioning, 8-bit RGB color values for visual information, and SNR values for assessing the accuracy of measurements. This comprehensive dataset is tailored for AI-driven analysis in robotic welding, enabling precise modeling and improving the effectiveness of welding robots in real-world applications.

E. Annotations and Metadata

All data captured during system operation were stored in Robot Operating System 2 (ROS2) bag files, which included topic names and message types for easy access and organization. This allows for efficient retrieval of the data during analysis and model development. Some examples of the topics in the ROS2 bag files include:

- **points/xyzrgba** - For point cloud data, which includes spatial coordinates and RGB color information.
- **color/image_color** - For RGB images, capturing the visual appearance of the scene.
- **depth/image** - For depth images, which encode the distance of objects from the camera
- **situation/name** and **relation/name** - For identifying specific scenarios and relationships between objects in the scene.

Additional metadata captured during the data collection process includes object coordinates, camera distance, and configuration details, providing valuable context for each dataset entry. This rich set of metadata enhances the ability to track and manage the data, ensuring that all relevant factors are considered when developing AI models for robotic welding tasks.

IV. Future Steps and Objectives

A. Preprocessing and Point Cloud Registration

One of the critical future objectives is to enhance the point cloud registration process, which aligns the captured 3D point cloud data with CAD models of the objects. This step is essential for ensuring spatial consistency and accuracy in downstream tasks. To address the challenges encountered during data collection, such as occlusions, reflective surfaces, and the differentiation of similar objects, hybrid approaches that combine traditional methods like Iterative Closest Point (ICP) [21] with AI techniques will be explored. AI-based orientation prediction models will assist in improving initial alignment for ICP, while deep learning methods will be trained to detect and correct occlusions and distortions in the point cloud [22]. Additionally, object detection algorithms will help in accurately identifying and associating similar objects with their corresponding point clouds. These advancements will form the basis for robust preprocessing pipelines, critical for preparing data for AI model training.

B. Data Augmentation and Clustering

To enhance the dataset's robustness and ensure model generalization, data augmentation techniques will be implemented. These include transformations such as rotation, and the addition of synthetic noise to simulate real-world variations. Data augmentation will help the AI models handle diverse welding scenarios and improve their reliability in unpredictable conditions. Alongside augmentation, clustering techniques will be applied to group point cloud data based on spatial and geometric features. This will assist in isolating key areas, such as welding zones, and improve the organization and labeling of data, ensuring efficient model training and testing processes.

C. Semantic Segmentation and Object Detection

The development of semantic segmentation [23] and object detection models will play a pivotal role in enabling AI-driven scene understanding. Semantic segmentation models will classify each point in the point cloud to distinguish welding lines, object edges, and background elements. These models will provide critical insights for accurately identifying welding profiles and trajectories. Additionally, object detection algorithms will be fine-tuned to detect and localize welding components within the scene. By leveraging these models, the system will achieve precise spatial awareness, which is essential for automating welding tasks

D. Model Training and Validation

The training and validation phases will focus on ensuring that the AI models perform reliably across various scenarios. The dataset will be divided into training, validation, and test subsets to maintain balanced representation and ensure robust model evaluation. Cross-validation techniques will be employed to minimize overfitting and maximize generalization. Performance metrics such as mean absolute error for spatial alignment, intersection over union [24] for segmentation accuracy, and precision-recall for object detection will be used to evaluate and refine the models. This phase will lay the groundwork for deploying AI models in real-world welding systems.

E. Weld Profile and Trajectory Identification

Another key objective is the development of algorithms for weld profile recognition and trajectory planning. By utilizing the outputs from semantic segmentation and object detection models, weld profiles will be accurately classified, and optimal welding paths will be determined. These trajectory planning algorithms will take into account spatial alignment, object geometry, and welding requirements to generate precise robot movements. This step will bridge the gap between data analysis and real-world robotic welding operations, enhancing the overall system performance.

F. System Integration and Deployment

The final objective is to integrate all AI models and algorithms into a fully functional robotic welding system, aligning with the principles of Intelligent Manufacturing and the vision of Industry 5.0 [25], which emphasizes human-centric, resilient, and sustainable industrial solutions. A real-time inference pipeline will be developed to dynamically process incoming data and generate welding trajectories on the fly. The system will be tested in both simulated and real-world environments to ensure reliability under varying conditions. Successful deployment will mark the transition from research and development to practical application, enabling automated and intelligent welding solutions in modern industrial settings and advancing the role of robotics in next-generation manufacturing ecosystems.

V. Conclusion

This paper highlights the transformative impact of AI-driven collaborative welding systems in advancing manufacturing efficiency and precision. By addressing key challenges and leveraging cutting-edge technologies, the proposed system offers a pathway toward more intelligent, adaptable, and sustainable welding processes. A pivotal advancement in this work is the introduction of an advanced data acquisition process, which underpins real-time adaptability and significantly enhances AI model performance. Future work will focus on refining system integration and expanding its applications across various industries.

Acknowledgment

This publication has been produced with the assistance of the European Union under project "Advancing Welding Innovations Through Artificial Intelligence (AI-WELD)". The contents of this publication are the sole responsibility of the Institute for Artificial Intelligence Research and Development of Serbia and can in no way be taken to reflect the views of the European Union. Also, this research was funded by the Institute for Artificial Intelligence Research and Development of Serbia, under the Seed Research Grant Program for young scientists (“Smart Manufacturing and AI-Driven Robotic Welding (SMARTWeld)”), through the financial support of the Serbia Accelerating Innovation and Entrepreneurship (SAIGE) Project, a joint investment by the Republic of Serbia, Ministry of Science, Technological Development and Innovation, the World Bank and the European Union.

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