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COMPUTER VISION-BASED ROBOTIC WELDING FOR CONSTRUCTION OF NUCLEAR POWER PLANTS

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ABSTRACT

Stainless steel is used extensively in construction projects of nuclear power plants (NPPs). Since they are primarily used as structural components, safety and quality issues related to welding are critical. However, despite its importance, the industry will have a deficit of 400,000 welders by 2024. In addition, the lack of welding quality can directly affect the safety concerns in NPPs. Therefore, there is a strong need to develop an automated robotic welding system to address the labor shortage and provide consistent and efficient welding. This paper presents a conceptual design of vision-based automated welding and a method for welding joint detection using visual sensors (e.g., a camera and light detection and ranging (LiDAR)) and a robotic arm. The results show that the weld seam and metal plates are correctly detected and distinguished using a deep learning algorithm.

INTRODUCTION

Labor Shortage in Welding

In the United States alone, more than 40 million tons of steel are used annually in the entire construction industry (Red-D-Arc Welderentals, 2020). Moreover, steels make up important structural components. Therefore, the quality of weldings is critical to the construction of facilities, such as nuclear power plants (NPPs) (Red-D-Arc Welderentals, 2020). However, the industry has struggled to attract the younger generation to become welders despite its importance. For instance, the American Welding Society (AWS) expects the welding shortage will reach a deficit of 400,000 workers by 2024 (Tradesmen International, 2019). Therefore, there is a need to develop an automated robotic welding system to address the labor shortage.

Welding Quality Issues

The nuclear industry and other stakeholders should be confident in the quality and integrity of welded joints, particularly since the next generation of nuclear power plants has a design life of at least 60 years (The Royal Academy of Engineering, 2012). However, there have been several safety issues due to the welding defects, which can directly affect the safety issues in NPPs. For instance, the licensee found more than 200 pounds of boric acid crystals on the containment floor at V.C. Summer Nuclear Power Station in 2000 (U.S.NRC, 2020). They identified a circumferential indication of primary water stress-corrosion cracking (PWSCC) in the first weld between the reactor vessel nozzle and the "A" loop RCS hot leg piping. In addition, five circumferential indications were found in three dissimilar metal (DM) welds on the pressurizer at the Wolf Creek Generating Station in 2006, which raised safety concerns due to the indications' size and location (U.S.NRC, 2020). Therefore, robotic welding is needed to provide a high welding quality with a consistent and efficient welding process.

Overview of Automated Mobile Robotic Welding System

This paper presents a vision-based and automated robotic welding system that consists of a robotic arm, unmanned ground vehicle (UGV), visual sensors, and a welding machine. This research includes the hardware integration of embedded platforms, sensors, and networking with visual sensors for machine vision. The planning of the development of software will include the design of a simulation environment, integration of visual Simultaneous Localization and Mapping (SLAM) algorithms, and design of feedback and motion planning strategies. As a result of this research, these components will be incorporated into a platform that will navigate autonomously on a construction site while creating a map of the surrounding environment and following a trajectory generated automatically from a user-defined target destination, detect welding joints using a visual sensor, and perform welding. Figure 1 shows the overview of the automated robotic welding system. As shown in Figure 1, the research process is divided into three main

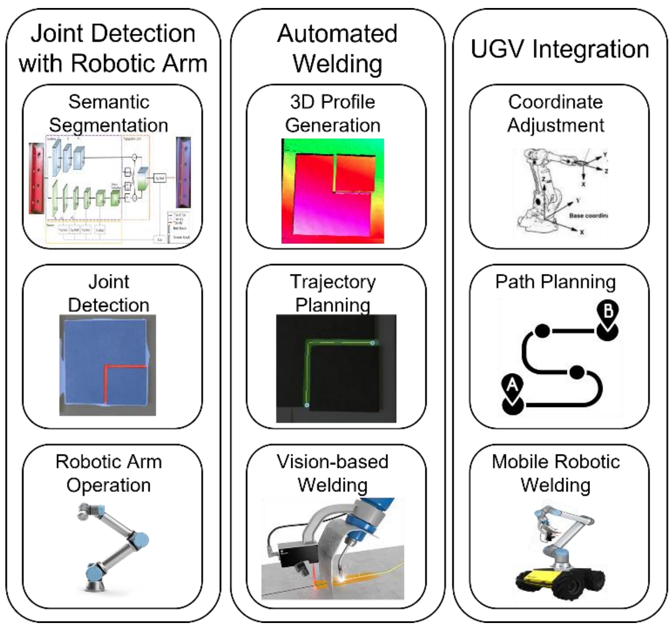

Figure 1. Overview of an automated mobile robotic welding system

phases:

1. Joint detection with robotic arm: Developing a method for automatically detecting welding joints with visual sensors and aligning a robotic arm to the detected joints through the use of deep learning algorithms
2. Automated Welding: Developing an algorithm to control the path along the joint and to perform welding using the robotic arm with the data acquired from the 3D scanning
3. UGV Integration: Developing an automated mobile system using the UGV by the coordinate integration, 3D mapping, and navigation

The system design of each phase is described in detail in the following sections.

SYSTEM DESIGN 1: JOINT DETECTION WITH ROBOTIC ARM

Joint Detection Using Deep Learning

In several areas and complex data from different sources (such as visual, audio, medical, social, and sensor data), deep learning methods have been demonstrated to outperform previous state-of-the-art techniques (Voulodimos et al., 2018). The algorithm has been developed primarily in the context of computer vision problems, including human pose estimation (Chen & Yuille, 2014), semantic segmentation (Noh et al., 2015), object recognition (Nie et al., 2018), motion tracking (Noghabaei & Han, 2021), and action recognition (Lin et al., 2016). In this study, two different types (butt and corner joints) with three different shapes (straight line, round, and L-shape) of welding joints, as shown in Figure 2, are trained using a bilateral segmentation network (BiSeNet) V2 (Yu et al., 2018), an effective and efficient solution for semantic segmentation that offers a good balance between accuracy and speed.
First, 330 images of each joint are collected: 200 for training, 100 for validation, and 30 for the test dataset. Then, the images in each training dataset are labeled in six classes: background, L-shaped joint, straight-line joint, round joint, corner joint, and metal plate. The outputs contain annotation files (.json) and a converted version of the polygonal annotations of the joint dataset as images whose pixel values represent ground truth. They are trained using 3-fold cross-validation, as shown in Figure 3. Each of the four joint classes has 200 training images, so 800 images in each fold are trained.

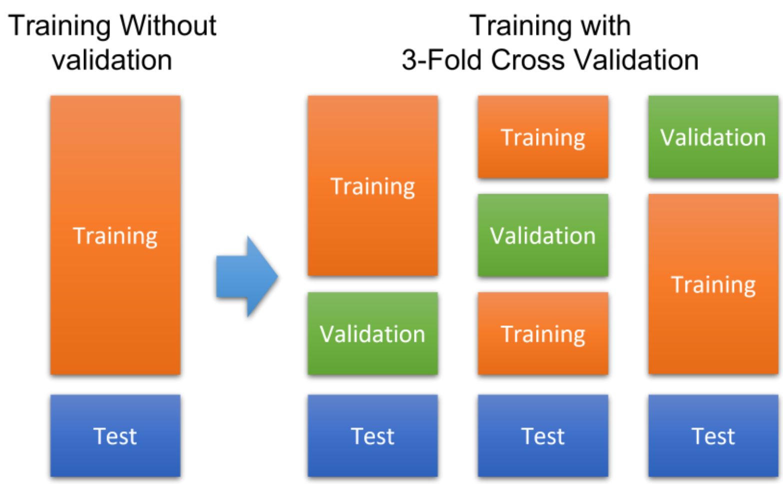

Figure 3. 3-fold cross validation method

The training time for 800 images with 1,000 epochs and eight batch sizes is around 25 hours by Alienware laptop (CPU: Intel Core i9-8950HK, GPU: GeForce GTX 1080 8GB, RAM: 32GB). The resolution of the training image taken by Samsung Galaxy Note 9 is 1024 x 512 pixels, and the resolution of the live video for the test by webcam, Logitech Brio, is 640 x 480. Figure 2 shows the test results of the

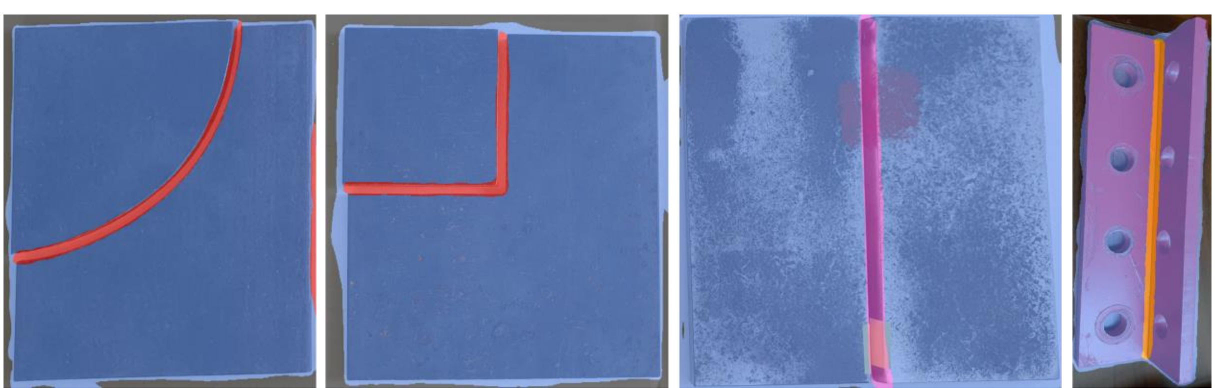
Figure 2. Results of welding joint detection using semantic segmentation

trained joint detector model. It depicts that each welding joint's weld seam and metal plate are adequately detected.

Robotic Arm Alignment and Scanning

Robotic arm alignment with the detected welding joint is essential for laser scanning. Once the robotic arm and the endpoint of the detected joint are aligned, the entire object can be scanned using the laser scanner attached to the robotic arm. The UR10e robotic arm produced by Universal Robots and Gocator 2350D laser scanner produced by LMI technologies are used for automated alignment and scanning. Two different methods for alignment are operated depending on the joint type in this study. First, when the butt joint is detected using a deep learning algorithm, the robotic arm tilts 30° for appropriate scanning of the weld seam. Otherwise, it stays in a top-down view. Following this, the robotic arm moves 1 cm per second in the x- and y-coordinates until the endpoint of the joint aligns to the center of the webcam view. Next, the laser scanner starts scanning and generating a 3D point cloud of the entire welding plate. Figure 4 shows the result of the 3D point cloud obtained by the laser scanner using automated robotic arm operation.

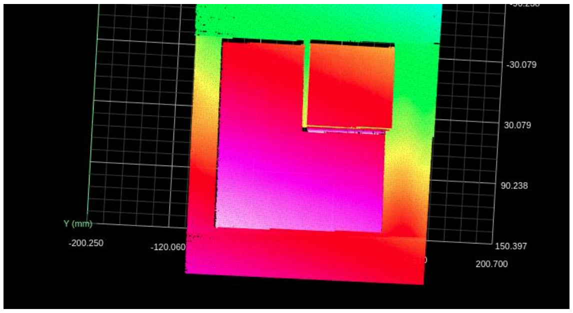

Figure 4. Result of 3D point cloud generation

SYSTEM DESIGN 2: AUTOMATED WELDING

Automated Welding Procedures

There are four main types of welding: Metal Inert Gas (MIG) – Gas Metal Arc Welding (GMAW), Tungsten Inert Gas (TIG) – Gas Tungsten Arc Welding (GTAW), Stick – Shielded Metal Arc Welding (SMAW), and Flux-cored – Flux-cored Arc Welding (FCAW) (Iowa Valley Community College, 2021) For automated welding, MIG welding is the most suitable method to be operated with the robotic arm since it only needs one hand.

Figure 5 shows the procedure of automated welding using laser-scanned data. First, the robot scans the specific range (e.g., 0.5 m) before welding. Specifically, the 3D point cloud, shown in Figure 4, is generated as described in the previous chapter. Once the pre-assigned area is scanned, the robotic arm moves back to the start point of scanning, and the system plans the trajectory of welding. When the system detects the round joint, the circle's center can be calculated by the joint's curvature. Since the center of the circle and start/endpoints of the round joint are known values, the welding trajectory can be designed. This path planning with the curvature makes the robotic arm rotate through the given angle. In the case of the L-shape joint, the desired degree of rotating is fixed to 90°. The scanned data gives the distance to the curve so that the system can plan when the robotic arm will turn.

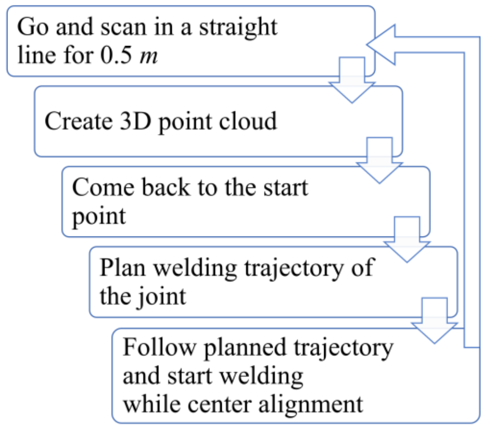

Figure 5. Procedure of vision-based automated welding

Robotic Arm Alignment for Welding Using Laser Scanner

In the previous chapter, the endpoint of the joint and the center of the live video view are aligned using the webcam. Whereas the center of the joint hole from the laser scanned data and the center of the actual joint hole are aligned using the laser scanner for welding in this chapter. The robot continuously aligns the center of the joint hole from the laser scanned data and the center of the actual joint hole while following the planned trajectory. For instance, the robotic arm will move 5 mm to –x direction if the center of the scanned joint hole is 5 mm away to the +x direction from the center of the actual joint hole (see Figure 6). The robotic arm slowly goes straight, and the welder starts welding while aligning.

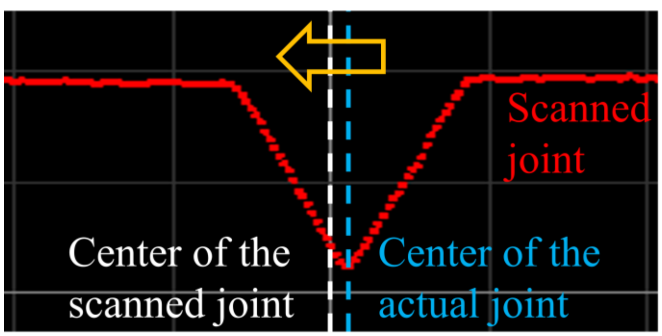

Figure 6. Method for joint alignment

Weaving Pattern

Proper parameters (e.g., welding weave patterns, welding speed, weld size, wire size, voltage, pre-heating, wire-speed, tip distance, and wire type) are selected by each other and other variables (e.g., workpiece thickness and workpiece material) (Moore, 2010). A welder setting chart is generally used to find proper welding voltage, wire feed speed, and welding current depending on workpiece thickness and wire sizes. However, the weaving pattern is varied depending on the joint type. For instance, the round weave is normally used for the butt joint, and V-weave is used for the corner joint. Although there is a generally used weaving pattern for each joint type, most welders use weaving patterns based on their preference. Therefore, the most widely used nine weaving patterns are developed using the robotic arm. Figure 7 shows the robotic arm operation for creating weaving patterns. To avoid any safety issues, a brush pen is used for testing the performance. The thickness of the drawn pattern stands for the pressure of the tip, which is one of the critical variables for actual welding.

Figure 7. Robotic arm operation for creating weaving pattern with brush pen

SYSTEM DESIGN 3: UGV INTEGRATION

Design of the Complete Mobile Welding Robot

Building construction mainly employs welding in the creation of structural frameworks from metal components (Lee et al., 2018). Welding is primarily used for connecting steel I-beams, trusses, columns, and footers to support the walls, roof, and floors of a building. These huge metal components cannot be welded using a fixed robotic system of the previous chapters. This chapter describes the integration of a UGV with a previously developed welding robotic system to add mobility to the welding robot.

By integrating UGV with the developed welding robotic system, the limitation of movable ranges become unlimited to the *x* and *y*-axis, as shown in Figure 8. This complete proposed robotic system can physically cover most of the structural components on the ground in the construction project. The trajectory plan for UGV, the lift kit, and the robotic arm will be re-designed to perform scanning and welding tasks for large metal components. The study on portable and automatic welding systems will be conducted by integrating diverse technologies such as the camera, the laser scanner, the robotic arm, the welder, the LiDAR, and the UGV.

Mapping and Navigation

To make the robot move to the desired position, map generation using LiDAR is needed. This sensor generates light energy reflected from various surfaces where the LiDAR sensor measures the return energy. With the information of the direction and range of the laser beam, in conjunction with the device's position the sensor is attached to, a 3D representation of the desired space can be formed (National Oceanic and Atmospheric Administration, 2021). Gmapping, one of the most widely used Simultaneous Localization and Mapping (SLAM) methods, is used in this research.

Since the LiDAR is attached to the UGV, Husky produced by Clearpath in this research, both odometry and Inertial Measurement Units (IMU) data from the UGV are used for mapping with point cloud generated by the LiDAR. As a preliminary test for mapping, the RPLiDAR, the 2D LiDAR produced by SLAMTEC, is used for generating a 2D map (see Figure 9). For better performance, Velodyne VLP-16 3D LiDAR will be used to generate the 3D map. After generating a map, the robot can be moved to any desired position in the generated map. A collision avoidance using RGB-D camera is also included in the system to avoid obstacles while navigating.

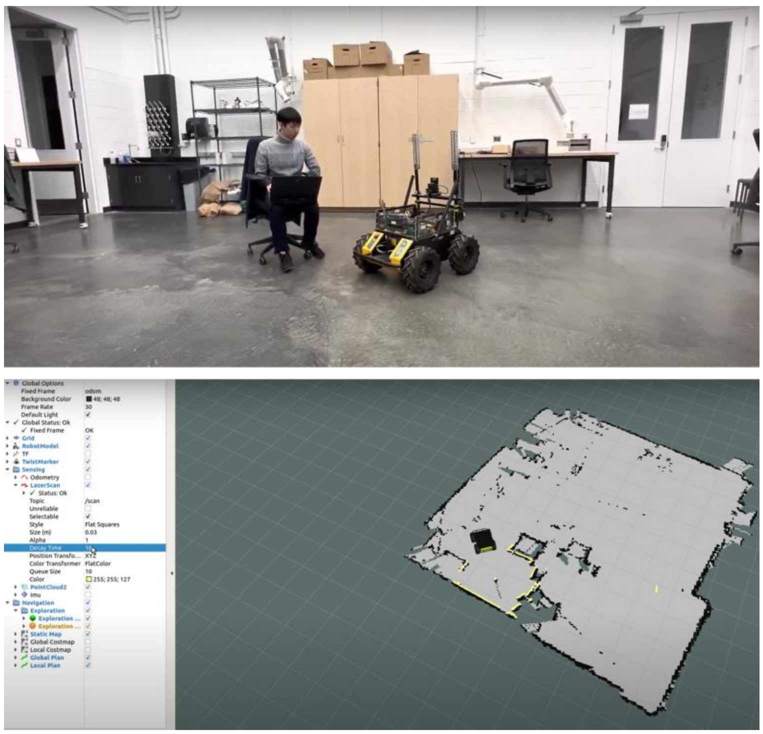

Figure 9. 2D mapping using UGV and LiDAR

Figure 8. Conceptual design of complete mobile welding robot

CONCLUSION

This paper proposes a conceptual design of a vision-based automated mobile robotic welding system by integrating visual sensors (e.g., webcam, RGB-D camera, laser scanner, and LiDAR), robotic arm, welding machine, and UGV. Since this paper presents the conceptual design, it still lacks details in some of the tasks. In addition, the light interruption from the actual welding work can be a severe challenge to the visual sensors' input. The visual sensors are sensitive to light conditions that derive massive joint detection and tracking error. Therefore, a metal plate between the welder and visual sensors will be added to isolate their light environment. The actual welding will be performed once the other parts are ready to be performed in the future.

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