Toward Total Welding Quality Management System based on Shipbuilding Monitoring System

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Abstract

The authors aim to develop a "monitoring and visualization system for shipyards" that will contribute to improving the efficiency of the ship construction process. The system focuses on the management of welding operations. It aims to enhance the quality control of welding by collecting and utilizing information on welding operations. The system collects digital data on the status of preparation, execution, and finishing of the welding process by monitoring video images, using an Internet of Things (IoT) smart cart that collects data on the progress of welding operations, and using smart glasses that allow workers to remotely set and check the welding current and voltage values. In addition, to detect abnormalities in the welding quality, a prototype device that can monitor the voltage and current of a welding power source with high precision was developed. Furthermore, an artificial intelligence-based judgment system that visually inspects welding defects based on the image information of the weld bead was also developed. The systems and devices described above were linked through integrated data. Thus, the PDCA (Plan-Do-Check-Action) cycle of welding operations could be accelerated, improving the welding quality control.

Keywords: Shipbuilding, Monitoring System, Welding Quality Management System, Cyber Physical System (CPS), Artificial Intelligence (AI), Internet of Things (IoT)
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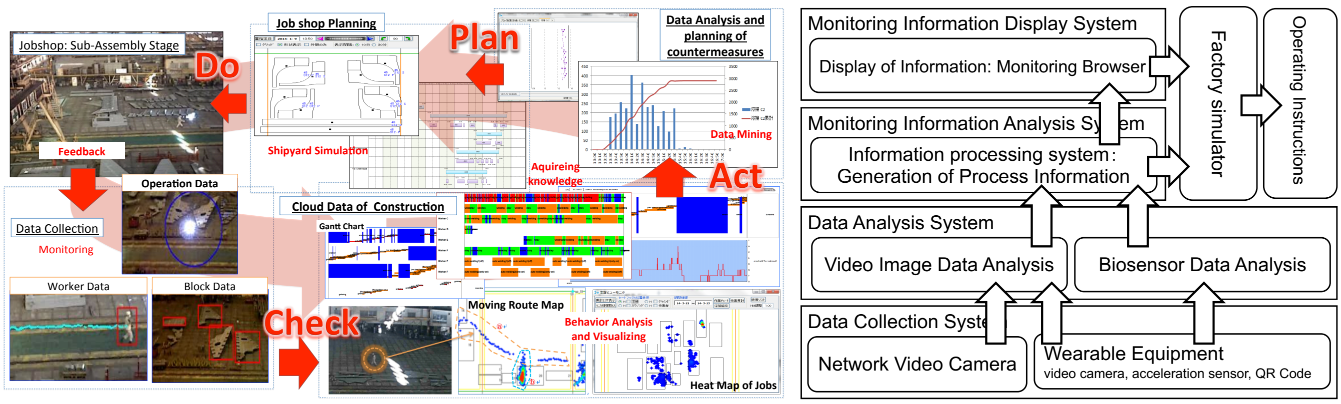
1. Introduction

In recent years, Internet of Things (IoT) and artificial intelligence (AI) have promoted the digitization and automation of production, and digital transformation is strongly expected in the production process. The authors have been developing a “Shipbuilding Monitoring System” (SMS) that uses video images and IoT devices to automatically collect digital information on welding [1]. It could detect abnormalities in operations and increase the utilization rate of production equipment and workers.

To improve the productivity, many kinds of data should be integrated into a cyber-physical system (CPS). This paper discusses the advancement of welding quality control through technology that collects, integrates, and utilizes data on welders and welding operations in shipbuilding.

2. Shipbuilding Monitoring System

Understanding the status of work in a shipbyard could effectively improve productivity. The proposed SMS can extract information about the work performance, as shown in Figure 1, from the video data captured by a video camera



(a) Plan-Do-Check-Action based on SMS (b) System Architecture of SMS

Fig. 1 Overview of shipbuilding monitoring system

installed in the shipbyard, including the position of the workers, welding operation time, and welding location. The system enables the detection of welding work and welding workers by object detection algorithms using deep learning. These techniques are undergoing innovation in driverless automobile technology (Figure 2) [4]. The latest algorithms (YOLOv5) have shown a stable object detection accuracy under various shooting conditions. They are capable of detecting grinding, gouging, and other operations in addition to welding operations.

Furthermore, the SMS has an additional function to build a multi-agent simulation (MAS) model by collecting data on the preparation, execution, and finishing of the welding process using the detected welder movement and welding location data. First, the reproduction of the welding process was simulated using MAS. The optimal conditions were then calculated to extract MURI, MURA, and MUDA of the welding process, which affect the weld quality [2].

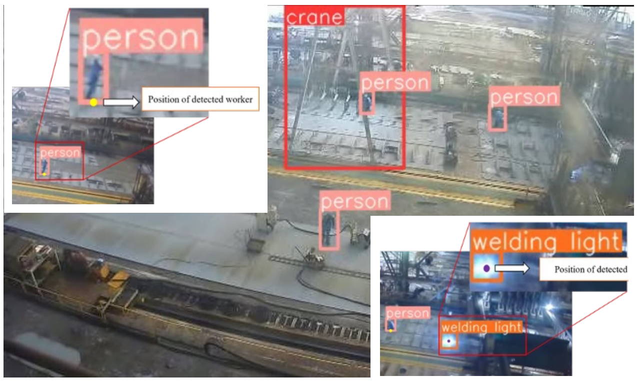


Fig. 2 Object (worker and welding) detection by YOLOv5

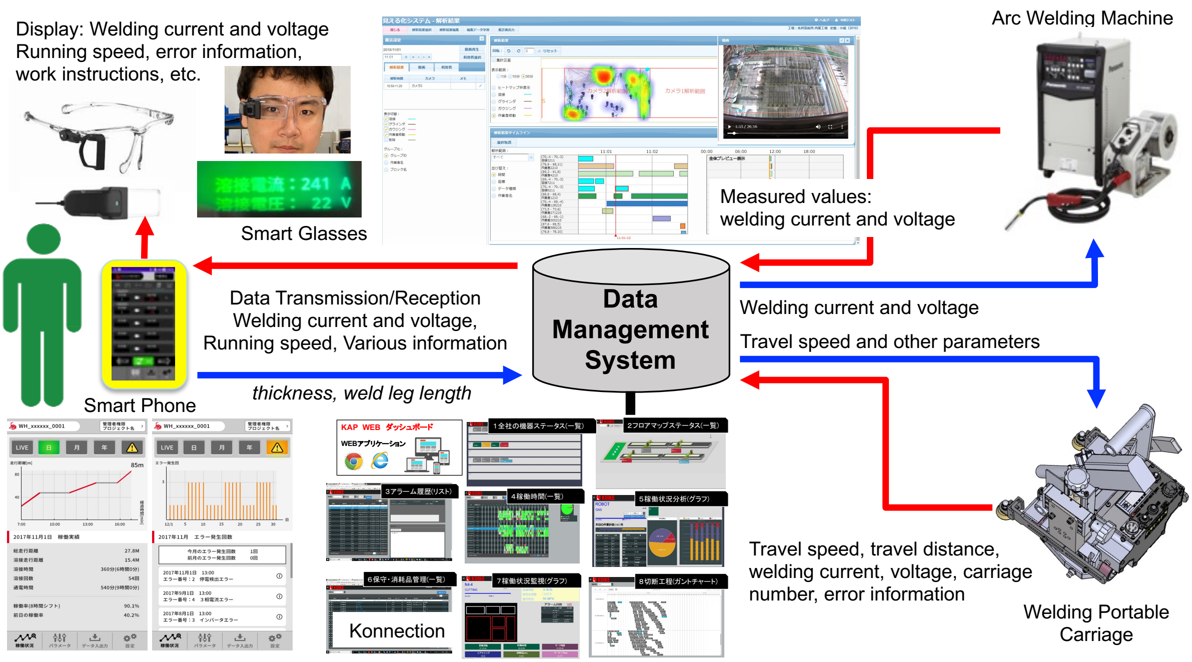


Fig. 3 Smart portable welding carriage and smart glasses

3. Smart Portable Welding Carriage and Smart Glasses

Most welding work in shipbuilding uses portable welding carriages. Therefore, we developed a system by creating a smart carriage and effectively utilizing the data collected by the carriage. Sensors and IoT devices mounted on the carriage collect travel log data (on, off, motor operation logs, etc.) related to the traveling and operating conditions of the carriage. In addition, data on the progress of welding operations and welding power source were recorded using the smart welding carriage (Figure 3) [3]. This data can be sent to the visualization system as digital data. A welding worker using the smart welding carriage can set the welding conditions of the carriage from a portable smartphone and check the smart welding carriage operation log. Data from the welding power source were managed via a smart welding carriage using the SMS. These running data and welding power data were integrated to develop the platform of the system for estimating weld quality during welding operations.

We developed a prototype of the smart glasses that enables the welder to remotely set welding conditions. These smart glasses can display information on the welding process, such as the welding voltage, current, and running speed of the cart. The welder can constantly check the welding status and confirm that the necessary work is being performed to ensure the weld quality.

4. Smart Device for Measuring Welding Current and Voltage

In welding, control of the welding current and voltage is critical for welding quality. A smart device for measuring the welding current and voltage was developed for analog welding power sources used in shipyards (Figure 4). The device utilizes a current/voltage sensor developed at the Purdue University in the U.S. It has a sampling frequency of up to 2000 Hz, making it highly accurate. The system incorporates a CPU that amplifies, digitally converts, and analyzes the signals from a probe that clamps the wire. The CPU is equipped with an AI function.

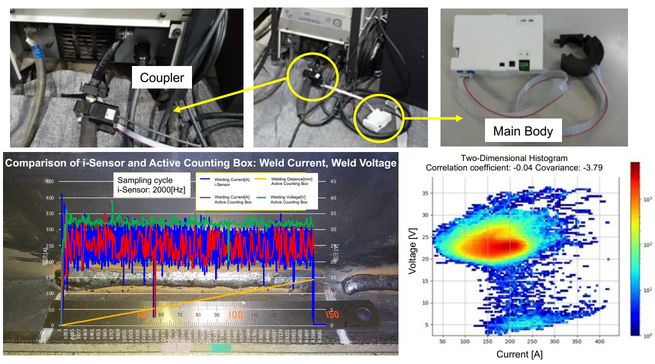


Fig. 4 Smart device for measuring welding current and voltage

This device can monitor the state of the welding process and build a basis for the monitoring system that can estimate weld quality based on the stability of the current and voltage. This device can be used as an anomaly detection system for the welding quality.

5. Judging Welding Quality by the Appearance of Weld Beads using Machine Learning

In shipbuilding, most visual inspections of the welding quality rely on the subjective judgment of the inspector. When a defective part is identified during an inspection after welding, the construction process is disrupted by rework. Therefore, a system that can immediately detect the presence and location of defects in a weld bead is desired. We developed a system for judging welding quality based on the appearance of weld beads using pictures and AI [4].

The accuracy of judgment using deep learning was examined by focusing on three types of welds and defects: overlaps, undercuts, and pinholes (Figure 5). The system was configured to train a judgment training model using training data consisting of approximately 1,000 samples/defect types. It also calculated the probability of the image being a defect from the weld bead image using this training model.

Three CNN models, VGG16, VGG19, and ResNet50, were compared and examined as training models. The model trained on ImageNet was used after the transfer learning. The probability of weld defects via machine learning was determined using binary classification to differentiate each of the three defects from a bead without defects. To improve the judgment accuracy, four types of preprocesses were considered: scale alignment, trimming near the bead, brightness adjustment, and grayscaling (Figure 5). The learning models were compared and evaluated using the “miss rate” as an indicator of the undetected defects. Table 1 shows the miss and correct response rates at appropriately set threshold values.

The relationship between the threshold value, correct response rate, and miss rate confirms the importance of setting the threshold value appropriately. Hence, the miss rate is suppressed while the correct response rate is increased. In particular, the maximum accuracy was 7.0% for the miss rate

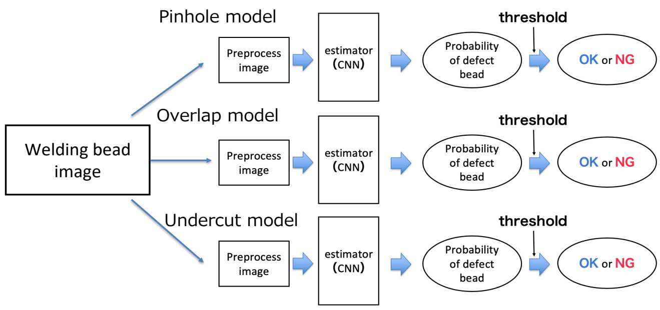


Fig. 5 Judging welding quality by the appearance of weld beads using machine learning

and 88.8% for the correct response rate when classifying pinholes.

6. Conclusion and Future Works for Integarted Welding Quality Management System

In this study, we examined the application of digital transformation, including IoT and AI technologies, which has been widely researched in recent years. We built a prototype system and verified its practical feasibility, although only partially. Finally, we summarize our expectations for the future. Large vessels are welded structures completed by connecting a number of steel plates using great amount of welding. The management of welding work plays an important role in their construction. From the viewpoint of welding construction management, it is important to collect information on welds before, during, and after welding construction. It is crucial to uniformly implement construction management quality control.

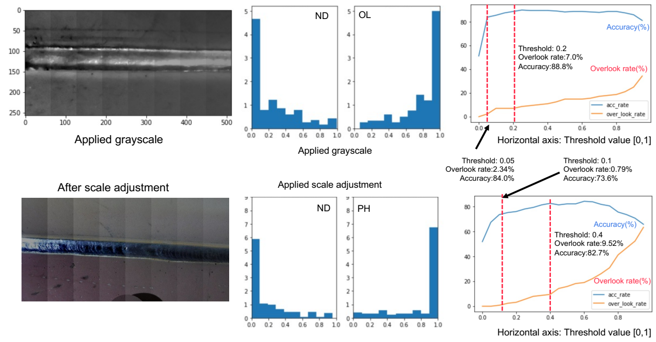


Fig. 6 Image pre-processes

Table 1. Results of learning model comparison

	DATA AUGMENTATION	VGG16	VGG19	RESNET50
OVER LAP	YES	72.1	**75.8**	**79.1**
	NO	**75.6**	72.2	78.4
PINE HOLE	YES	**81.2**	**78.9**	82.9
	NO	72.4	73.6	82.7
UNDER CUT	YES	**62.1**	61.3	**58.3**
	NO	50.2	**70.3**	53.6

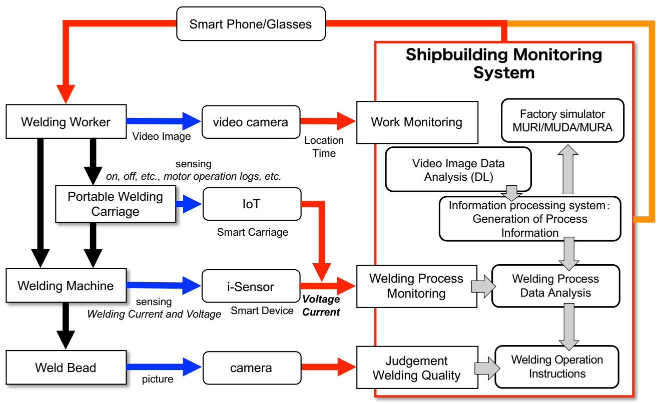


Fig. 7 Welding Quality Management based on SMS

In the pre-construction stage, measurement data on installation accuracy, such as groove conditions and gap misses can be collected. During the welding stage, it is desirable to collect process-monitoring data that can confirm the current and voltage of the welding power source, defects, defective melting, and other conditions. Even in the post-construction stage, it is desirable to be able to easily collect data on the weld leg length, beads, etc., in relation to weld quality inspection. Although each of the weld data collected in this study are local data, they are expected to be useful for the weld deformation of steel structures and simulation techniques of welding processes. These data are expected to provide critical information for welding life cycle management and traceability of quality.

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