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Bringing Machine Intelligence to Welding Visual Inspection: Development of Low-Cost Portable Embedded Device for Welding Quality Control

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Abstract

Welding is commonly used for connecting metal components in these critical metallic infrastructure, such as agricultural facilities, wind turbines, railways, bridges and pipelines. However, welding processes vulnerably lead to forming cracks, pores, and other defects on the surface. These defects not only could result in severer cracks and corrosion, but also may ultimately lead to malfunction and failure of metal components. Inspection of welds is thus critical to ensure the welding quality during fabrication, construction process, and later in-service stage. The visual inspection is the crucial and most cost-effective step to determine if the welding quality is passed or rejected. However, fast and accurately determining welding quality is a challenging task in the conventional visual inspection process, which is highly dependent on the experience and expertise of inspectors, and it is fairly subjective and sometimes even misleading. To meet the gap, we bring machine intelligence to welding visual inspection. Specifically, we developed a low-cost portable embedded device to support advanced machine learning algorithms for real-time welding image processing.

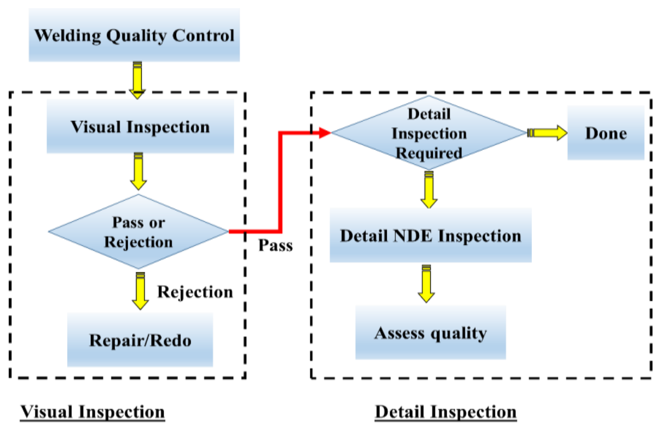

Figure 1. Flowchart of welding quality control (visual inspection and detail inspection) and application of the proposed device to visual inspection.

INTRODUCTION

Critical metallic infrastructure, such as agricultural facilities (e.g., tanks and storages), wind turbines, railways, bridges and pipelines, is a key lifeline as a network for economy and society need. Welding is commonly used for connecting metal components in these critical metallic infrastructure during fabrication and/or construction. Welding processes require high heating input while various factors, such as shrinkage of weld/parent metal or overheating of joint, vulnerably lead to forming cracks, pores and other defects on the surface. These defects not only could result in severer cracks and corrosion, but also may ultimately lead to malfunction and failure of metal components. According to data from the Federal Railroad Administration, broken rails and welds are the leading cause of train derailments, accounting for over 15% of derailments. Inspection of welds is thus critical to ensure the welding quality during fabrication, construction process and later in-service stage.

Fig. 1 shows the typical welding quality control, includes two steps: i) *visual inspection* and ii) *detail inspection if required*. Visual inspection is the first step and it is also the critical and most cost-effective method for welding quality control. It is usually performed by certified welding inspectors who have certified training in welding quality control and defect assessment. During the visual inspection process, over twenty different categories of welding imperfections on the suffice, such as cracks, porosity, inclusions, lack of penetration, lack of fusion, undercut, insufficient weld throat, and misalignment, will be considered to determine if a welding is passed or rejected. If rejected, the defect information is provided for a redo. If passed by visual inspection, the detail inspection is needed for hidden defect study. In the detail inspection process, nondestructive examination/testing (NDE/NDT) methods such as ultrasonic testing (UT), radiographic testing (RT) and magnetic particle inspection (MT), and phased-array ultrasonic technology (PA-UT), are applied to extract hidden defect information. However, this process requires extensive skills in operating those expensive equipment and complicated data interpretation, thereby resulting in much higher cost and longer inspection time. Accordingly, an effective first-step visual inspection process will significantly enhance the cost-effectiveness and enable rapid decision making for welding quality control.

However, fast and accurately determining welding quality is a very challenging task in today's visual inspection process. First, the threshold acceptance criteria is complex, which is dependent on precise defect information (e.g. shape, size and location) collection. For over twenty different weld defects, they have their own characterization from appearance to texture and therefore each category of defects has specific threshold acceptance criteria. Second, the current relied hand tools for visual inspectors are unable to provide accurate and rapid measurement. Different from detail inspection with advanced equipment (e.g. UT, RT, PUT) available, visual inspectors still rely on hand tools for defect measurement, which is difficult to collect accurate information fast, sometimes even fairly subjective and misleading. Third, with the shortage of welding visual inspectors, today's workforce is aging. Last, but not least, for many welding locations such as tall buildings or bridges, it is not easily accessible for visual inspectors.

In this paper, we bring machine intelligence to enhance visual inspection in welding quality control by developing a low-cost and reliable portable embedded device with advanced machine learning techniques. Our developed device significantly enhances the effectiveness of visual inspection, which will further enable rapid and cost-effective decision making for welding quality control.

PROPOSED TECHNIQUE

We developed a low-cost portable embedded device for fast image processing with advanced machine learning techniques, thereby providing real-time defect information aiding visual welding inspection.

Fig. 2 shows an overview of our technology. It mainly consists three parts: (i) designing machine learning algorithms for accurate defect information extraction and decision making, (ii) implementing the developed machine learning algorithms on embedded device, and (iii) developing a portable device with custom system design and optimization. The implementation details for each part will be provided in next section.

IMAGE PROCESSING AND DECISION MAKING

We have developed new image processing and machine learning algorithms for defect information extraction and classification with high reliability.

Specifically, instead of using one picture as in our preliminary study, two pictures are captured as input images in our new algorithms. These two pictures have the same camera position but different angle of light. First, we convert two pictures into grayscale. For grayscale pictures, RGB values of each color are the same, and the brighter the color is, the values of RGB are greater. Fig. 3 shows the two pictures are composited using the input pictures. First picture is composited using the absolute values of the subtraction of pixels on the same position from two input pictures, which means the closer the brightness of input pixels are, the darker the composite pixel is. Using two images, we can extract a clear boundary for the weld bead on the first composite picture. Second picture is composited simply taking the brighter pixel on the same position from two input pictures. The defects maintain darker color for different angles of lights. Hence, the second composite picture has a clear vision on defects. From two composite pictures, two binary images are generated. First binary image can be used for boundary detection, and by applying the boundary to second binary image, noises located outside of the boundary are eliminated, which significantly enhance the reliability of extracted defect data.

Based on the extracted defect and welding size information, we have developed a new machine learning algorithms based on Support Vector Machine (SVM) to classify the types of defects. First, we train a SVM model based on various classified training welding images. During this process, the pictures need to be divided into many cells, and apply SVM algorithm to get the

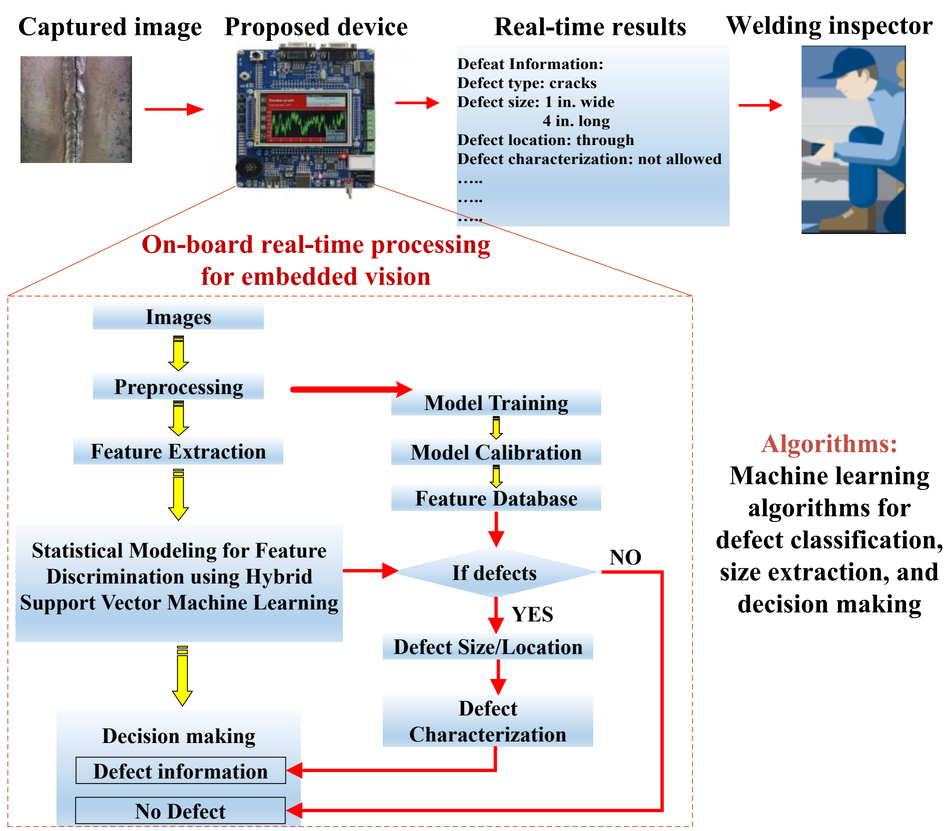

Figure 2. Proposed technique.

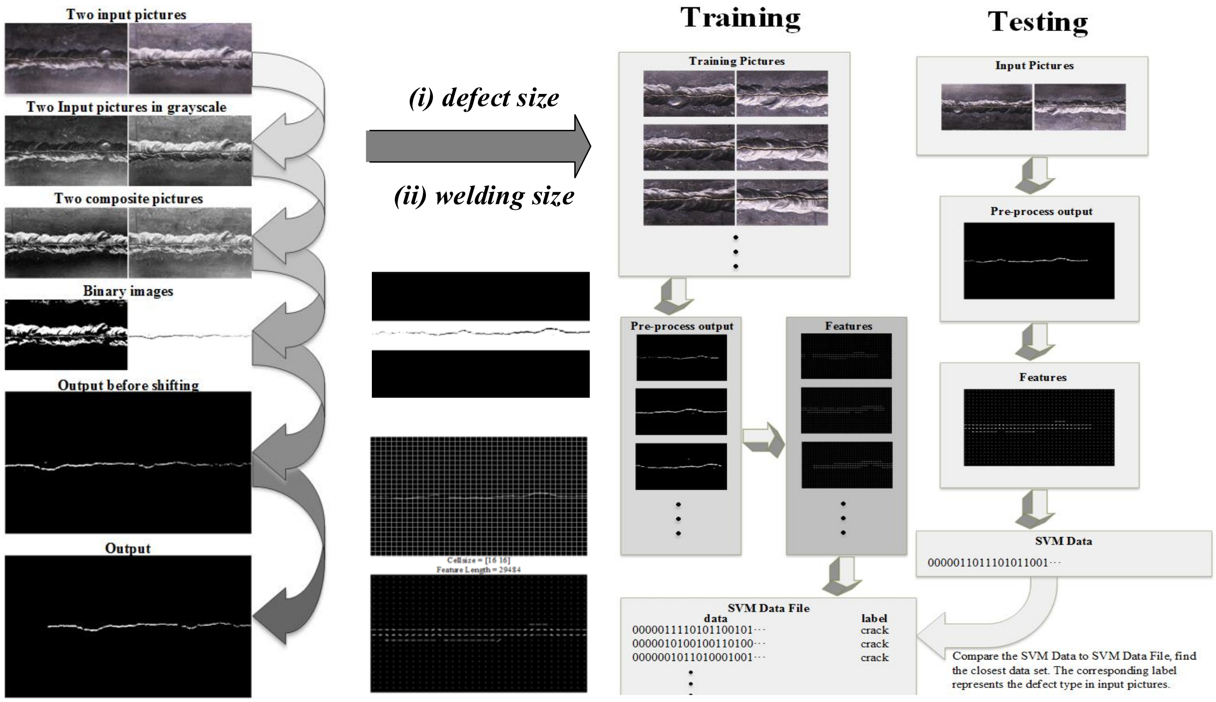

Figure 3. Developed image processing and machine learning algorithms for reliability enhancement.

features for each cell, and record these features. Then, we label the features based on the defect type of training image. All the features with labels are stored as a lookup table. The features for input images to be classified need to be compared with the training feature lookup table. The defect type label corresponding to the closest training features in the lookup table decides the defect type in the input image.

During this process, a major challenge is that if the defect is not at the center of the image, how to enhance the reliability of the classifier. To solve this, in this project, we develop a displacement algorithm to shift the defect to the center of image. A Binary Large OBject (BLOB) is a single entity binary data, a chunk of white data in this case. Use the central point of the largest BLOB as the central point of the shifted image (see Fig. 3). After shifting, the SVM classifier can classify the defect type correctly.

DEVICE PROTOTYPE

Fig. 4 shows the developed device prototype, based on Raspberry PI with quad-core Cortex A53 processor, which consists of Raspberry PI processing board with quad-core processor, camera, display, and battery. The developed SVM based image processing and machine learning algorithms can achieve high reliability. However, its computing process is very intensive, requiring a long processing time based on the resource limited embedded system platform. To overcome this challenge, we completely designed the C++ code for machine learning algorithms without availability libraries. In addition, we designed a multi-core scheduling technique to schedule instructions to different processor cores. The algorithms can be completed and display the results within 1 second.

In order to enhance the reliability of the developed device, we have optimized the device and developed an enclosure using 3D printing technology to fit different welding shapes with light interference. As shown in Fig. 5, the wings on the sides of the box are used for welds with different shapes.

We have used different welding samples made in NDSU Machine Shop for lab testing. As shown in Fig. 6, the device works well for different defects with high reliability and generates the results within 1 second.

CONCLUSIONS AND FUTURE WORKS

In this paper, we have developed a low-cost and reliable portable embedded device with advanced machine learning techniques, thereby bringing machine intelligence to enhance visual inspection in welding quality control. This technology has great potential to benefit welding quality control due to the concept of low cost and speed, which will ultimately improve the quality and thus structural safety of civil metallic infrastructure. As our future work, we plan to integrate our device to Unmanned Aerial Vehicles (UAV) platform as a payload; we also plan to integrate sensing technology (e.g. infrared camera or x-ray sensor) with the developed device to investigate the hidden defects for detail inspection.

ACKNOWLEDGEMENT

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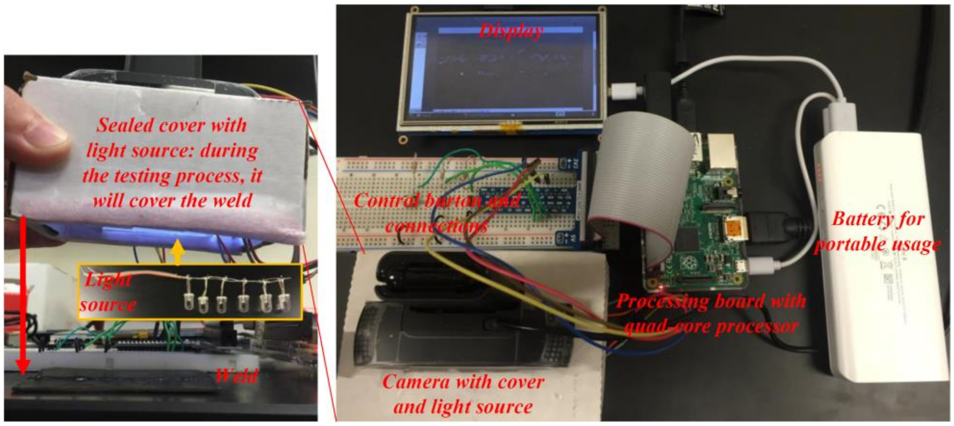
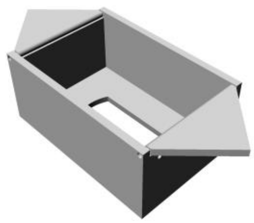


Figure 4. Our developed device prototype.



(a) enclosure 3d model

(b) enclosure

(c) screen and battery

(d) core device and pin connection

Figure 5. Optimized device with enclosure

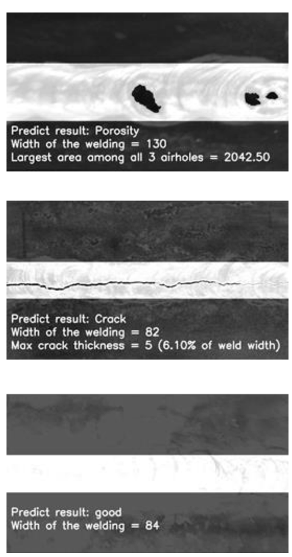


Figure 6. Testing results using different welding samples.