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Welding Quality Analysis Using Robotic Based System

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Abstract – Nowadays, competition in industrial production has come to the top with technological improvements. In this competitive environment, producers need better quality, faster and less costly production methods. So, the use of industrial robotic systems is becoming increasingly widespread for different sectors. In this experimental study, the advantages of robot welding automation compared to manual welding process were analyzed. Particularly, the difference between the two processes in the welding trajectory is constantly changed, is revealed as a result of the tests. In this study, Kuka KR6 industrial robot manipulator is used for experimental welding process.

Finally, according to result of the experiment, the welded workpieces obtained from the robotic welding process and the operator manual based welded workpieces are compared. The quality difference between two processes is better observed because the frequency of the trajectory changes frequently in the weld seam in the square wave form. In order to better evaluate the results of this work, the resulting parts were subjected to a tensile test in a laboratory environment. The test results showed that robotic based welding has superior performance for joint two steel plates.

Keywords – Robotic arc welding, Industrial Robots, Mechatronics System, Automation.

I. Introduction

Despite technological advances, many undesirable faults can ocur, especially in robotic welding process. As a result, faults such as cracks, depositions, stacks, particle faults are observed especially in workpieces with variable trajectory weld seams. The studies carried out in order to automatically detection the weld seam is one of the investigations made to produce this solution of the problems.

Some of significant papers have remarked about these problems. Numerous researches have focused on automatic weld seam identification [1-3]. [4] were present a new weld joint detection method using stereo vision system for automatically generate programme paths. This approach was experimentally tested on an industrial robot manipulator.

[5] controlled the welding parameters to obtain optimum welding qualities in the robotic gas metal arc welding using artificial neural network technique. For this reason, the accuracy of the results is compared with the neural network models developed using two different learning algorithms, the Error Backpropagation algorithm and the Levenberg-Marquardt algorithm. In the experimental study, weld width information was used at the output layer while parameters such as number of passes, welding speed, source current and arc voltage were set as inputs to the artificial neural network model.

[6] were produced a methodology to fault detection on robot manipulators using neural network. This approach was tested on KUKA six-axis robot manipulator. The obtained results have been extremely effective in determining these faults that are vibration based.

This experimental study mainly involves scientific work on the development of methods for minimizing weld faults for the robotic welding process which is extremely important for industry. Operator-based weldings are more stacked and there are welding faults that go out of trajectory. In addition, due to very good arc can't be provided, and faulty and re-necessary welding can also occur. For this reason, in this experimental work, research and development will be carried out on a fully automated and camera image system and a very good performance and quality welded joint.

The paper is organized as follows: Section 2 present the experimental system and used methods. In Section 3, test results are analyzed. Finally, this study concluded and discussion in Section 4.

II. Materials and Method

The experimental study in this paper was carried out in the mechatronics systems laboratory. The general appearance of the experimental system in the laboratory is shown in Fig 1. The system fort he experimental work consists of the following equipment :

- Industrial Robot Manipulator
- Welding Equipment
- Steel Table
- Test Sample
- Camera
- Computer for image processing and control

In this experimental study, KUKA KR 6-2 is used as industrial robot that it has six degrees of freedom. It is employed to analyze the optimal angles of joints as shown in Fig. 1. The robot manipulator are driven by electromechanical AC servo motors. Maximum speed of robot manipulator's end-effector is 6000 mm/s. The positioning repetition accuracy of the robot manipulator is 0.1

mm [7]. The axis features for the investigated KUKA robot manipulator are given in Table 1.

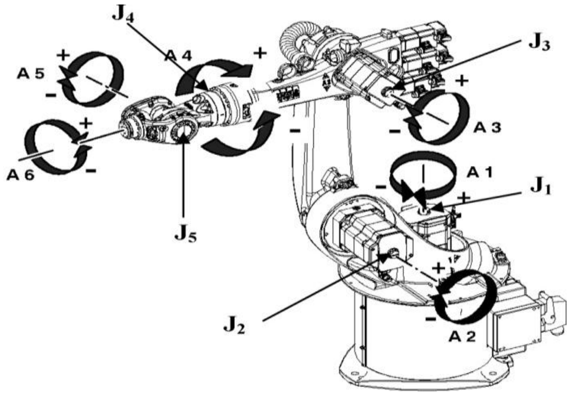

Fig. 1 Joints rotations definition of the Kuka robot manipulator [6]

Table 1. Kinematic parameters of the welding robot manipulator joints [7].

Axis	Range of motion	Speed
1	±185°	3000 d/d
2	+35° to -155°	3000 d/d
3	+35° to -155°	3000 d/d
4	±350°	6000 d/d
5	±130°	6000 d/d
6	±350°	6000 d/d

The experimental system as shown Fig. 2. that consists of a Kuka KR6 industrial robot manipulator, Fronius arc welding equipments, a high definition webcam type camera, a steel table and steel material pieces in different profiles for testing and computer are used to realize automatic robotic welding process. The workpieces was placed randomly position on the steel welding table top. Then, camera that mounted on the table capture the images. The captured images are corrected using image processing algorithms. Thus, robot path is generated automatically for welding process.

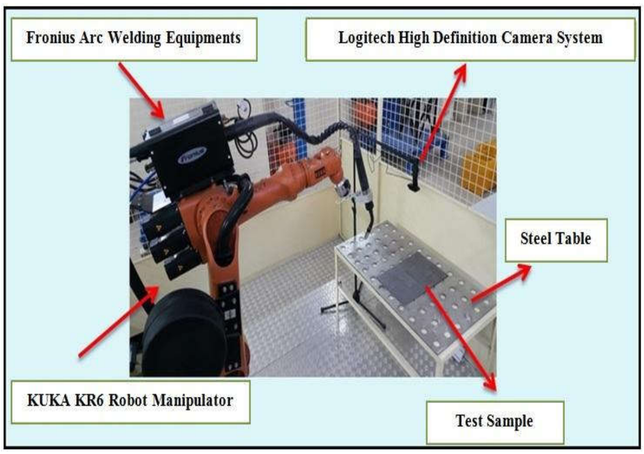

Fig. 2 Experimental system

A total of 20 pieces of alloyed steel materials with dimensions of 400x300 mm and 3 mm wall thickness have been manufactured to be used as a sample in the welding process of the experimental works. In addition, a table made of stainless steel material with a thickness of 20 mm for the base has been manufactured. This table was heat treated and surface tempered so that the samples did not weld and contrast difference. In addition to this, in order to assist in calibration and positioning in image processing, holes in certain form are opened on the table. The view at different aspect of the test specimens is given in Fig 3.

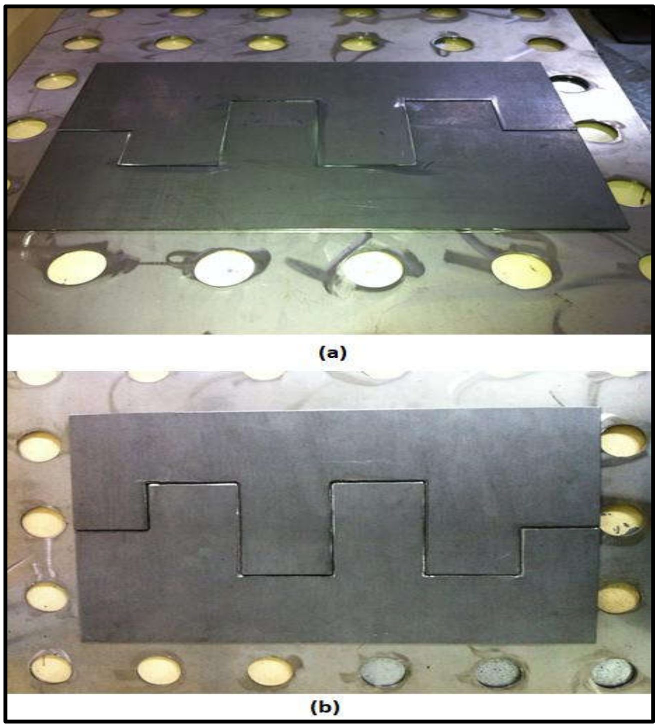

Fig. 3 Test sample- (a) perspective (b) top view

An overview of the automatically robotic welding method is presented in this section. (1) The first step is to capture image of the workpiece and seam determination using image processing. (2) The obtained image is trimmed to create input layer for training neural network model. Then, neural network predictor is generated to remove faults on the resulting image. (3) Finally, generated position data is sent to robot controller.

A. Weld Seam Detection

Firstly, it is captured image of the workpiece on the workbench and it is converted to grayscale as shown Fig. 4(a). The captured images are filtered using image processing algorithms via Matlab program for detect weld seam. Finally, weld seam trajectory is detected using prewitt edge algorithm as shown Fig. 4(b). The conversion from RGB to grayscale can be archieved using equation:

$$I_{gray} = \begin{bmatrix} 0.3 & 0.59 & 0.11 \end{bmatrix} = \begin{bmatrix} I_{rgb}\{R\}(u,v) \\ I_{rgb}\{G\}(u,v) \\ I_{rgb}\{B\}(u,v) \end{bmatrix} . \quad (1)$$

where I_{gray} is calculated grey image from the camera, (u,v) is the pixel co-ordinate, $I_{rgb}\{R\}(u,v)$, $I_{rgb}\{G\}(u,v)$, $I_{rgb}\{B\}(u,v)$ are the red, green and blue components of the left RGB image respectively [7].

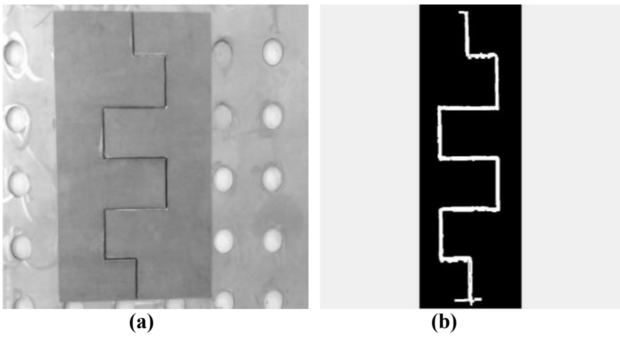

Fig. 4 Weld seam detection on the workpiece image

B. Image Enhancement

Unfortunately, only the image processing technique is not enough to determine the welding seam trajectory. As shown Fig. 4(b), there are some faults on the image. For this reason, a neural network predictor is presented for image denoising processing.

ANNs are commonly accepted intelligence research where a non-linear mapping between input and output parameters is required for a function approximation [5]. In this experimental work, feedforward neural network type is used and Scaled Conjugate Gradient (trainscg) function is selected for training three layered neural network model. Thanks to generated this model very successful results have been obtained by using a neural network estimator model to improve the faults on the picture using image processing, in Fig. 5. In these results have shown that neural networks can be used in this area.

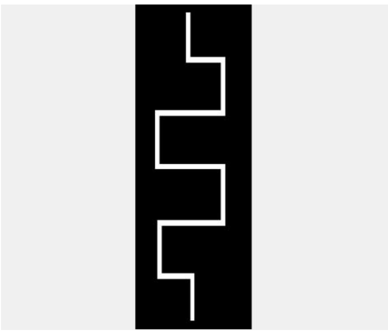

Fig. 5 Image denoising using neural network

C. Sending Data from Computer to KUKA

To find which of the weld joint and then to determine the motion points, new neural network predictor is developed in this study. The cartesian co-ordinates of the detected points are sent to the industrial robot controller via computer as axis angle values. This communication is provided by the developed new interface on the computer side using JopenShowVar. On the Kuka side, KUKAVARPROXY is used for data transfer [8].

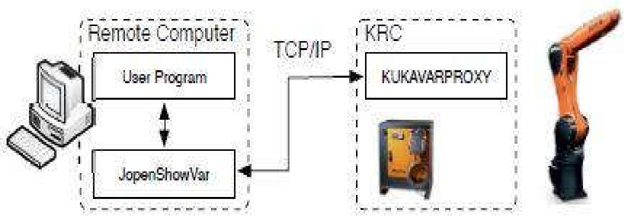

Fig. 6 Communication schema between KUKA and computer[8]

III. RESULTS

The result of the experiment is compared to the welded work obtained from operator manual based welded work. Fig. 7 shows an image of the obtained weld as a result of both processes. The picture on the left is the welding made manually by the operator and has many faults according to the welding made by the robot on the right. It has been observed that the quality difference between the two processes is further increased as the trajectory of the weld seam in the square wave form increases the difficulty of the process. In order to evaluate the results of this study more accurately, the workpieces obtained at the end of the application were tested by tension test.

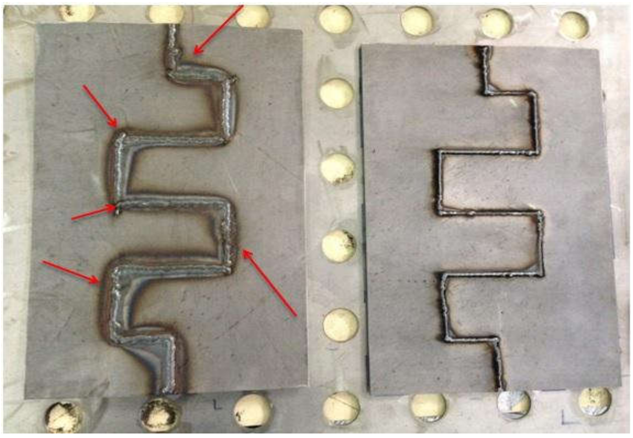

Fig. 7 Operator based manual welding and robotic welding

Since the workpieces obtained in the experiment are too large for the tensile test, samples are cut out in 60x40 mm sections on the part according to the limits of the test device. While the samples were being prepared, care was taken to take samples from the same sides of the parts obtained by both processes. The steps of forming the samples in the laboratory in which the experiment is performed are shown in Fig. 8.

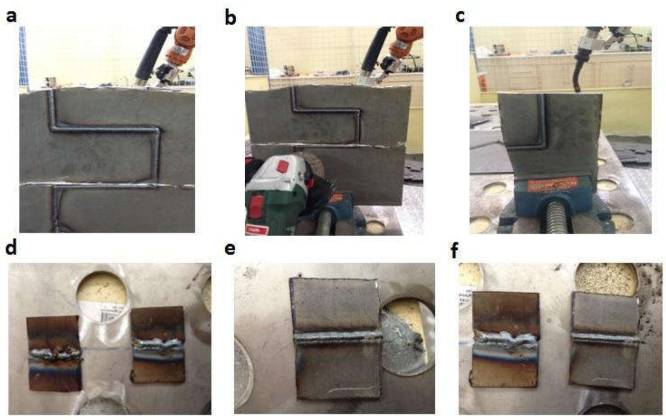

Fig. 8 The steps of forming the samples in the laboratory

The samples obtained after the experimental study were tested by Technology Research and Application Center of the University of Erciyes (TAUM). The test steps are shown in Fig. 9. In addition, the test speed is set at 5 mm / min.

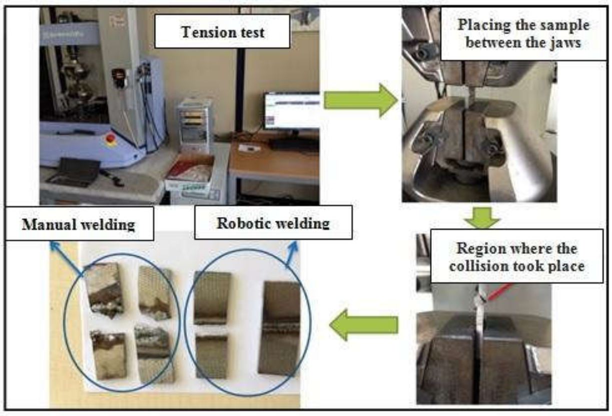

Fig. 9 Tension test steps in the laboratory

Fig. 9 and Fig. 10 show the stress-percentage elongation and force-percentage elongation graphs of the samples. As shown in Fig. 9, it can be seen clearly that the welded part of the robot is resist higher tension.

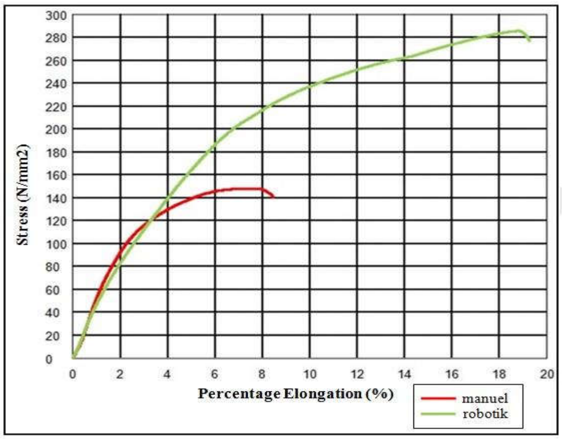

Fig. 9 Stress-percentage elongation graphs

When the force-percentage elongation graph was examined, it was observed that materials exhibiting similar elongation characteristics did not show any difference after 8000 N force value when a certain amount of the same force was applied. It can be seen that when the hand welded part is caught when approximately 8861 N force is applied, the part obtained by the robotic welding process shows resistance up to about 17100 N. In addition, when the sample taken from the hand-welded part has increased by about 1.99 mm at the end of the test, the sample obtained by the robotic welding process is measured after about 4.32 mm.

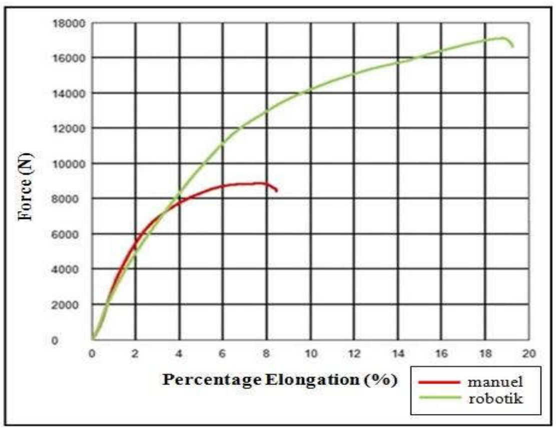

Fig. 10 Force-percentage elongation graphs

Numerical data of the tension test results are also observed in Table 2. According to these results, it has been proven that robotic welding process is obviously stronger than manual welding.

Table 2. Numerical data of the tension test results

Axis	Range of motion	Speed
Max. Stress (N/mm2)	147.684	285.009
Max. Force (N)	8861.02	17100.6
Max. Percentage elongation (%)	7.68502	18.7883
Max. Elongation (mm)	1.99810	4.32131
Max. Strain analysis (mm)	1.99810	4.32131
Elasticity module (N/mm2)	5451.16	4712.56

IV. CONCLUSION

The results obtained from the designed system are extremely successful in order to be an important probing solution encountered in the robotics welding process. With the development of the experimental work done, it will be possible to find solutions to the problems frequently encountered in robot welding automation, such as the detection of the automatic welding path which is frequently encountered in the industry, the determination of the starting point of welding, and the finding of nonstandard workpieces originating from manufacturing faults.

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