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USE OF ARTIFICIAL NEURAL NETWORKS FOR THE CORRECTION OF FAULTS ON THE DETECTED WELD SEAM IMAGE

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Abstract

Recently, the use of industrial robots has become widespread and the number of researches on this area has also increased considerably. Particularly the work done on robotic welding process is striking. Much of this work is about improving welding quality and automatically determining the welding path. Generally, 2D and 3D image processing methods have been used to determine the weld seam with various algorithms. Previous studies show that the biggest problem in this methods applied is the clear separation of the weld seam from the image. In this experimental study, artificial neural networks are used as a solution for this common problem. The most accurate result are obtained with the applied algorithms. It can be seen that the obtained results show the weld seam can be detected clearly using artificial neural networks.

1. Introduction

The use of computer vision technology in the industry is increasing day by day. In addition to this, a number of studies have been carried out in order to overcome some problems in this technology. Nowadays, computer vision technology is widely used in robotic arc welding process. This technology offers solutions to many problems such as automatic detection of weld seam and determination of initial point. It is also used to control the welding quality after the process. However, there are still some problems with image processing methods used to determine the weld seam. The most important of these problems is that obtained image isn't purely. A wide range of solution to this problem have been proposed by researchers.

Several researchers have focused on autonomous welding seam detection[1 2]. Jia Qin et al. used a cascade algorithm composed by medium value filter and homomorphic filter for reduce image quality drop. Thus, welding image denoising is purposed[3] . Yanling Xu et al. present a new improved Canny edge algorithm has been proposed to detect the edges of weld seam[4].

In this paper, artificial neural network are used to weld seam image denoising. The suggested methods provide separation of the weld seam from surface of the workpieces on the captured image. Experimental platform is constituted to test that the proposed method can be used for industrial implementations. The paper is organized as follows: Section 2 introduce the experimental platform. Section 3 gives some details the proposed methodology. The experimental and simulation results are given in Section 4. Finally, this paper concluded and discussion in Section 5.

2. Experimental System

The experimental system compose of a Kuka KR6 industrial robot that has six degrees of freedom, Fronius arc welding equipments, a high definition 1920x1080 pixels camera, a steel welding table and 30 steel material pieces as experimental pieces for testing and computer to run image processing. The workpieces was placed on the steel welding table top. Then, camera that mounted above the table capture the images. The experiment system is shown in Fig. 1. The captured images are filtered using image processing algorithms via Matlab program.

[1] X.Z. Chen, S.B. Chen, "*The autonomous detection and guiding of start welding position for arc welding robot*", Industrial Robot: An International Journal, 2010.
[2] Mitchell Dinham, Gu Fang, "*Detection of fillet weld joints using an adaptive line growing algorithm for robotic arc welding*", Robotics and Computer-Integrated Manufacturing, 2014.
[3] Jia Qin, Guohong Ma, Pei Liu, "*Image processing algorithm of weld seam based on crawling robot by binocular vision* ", 2011 IEEE Second International Conference on Mechanic Automation and Control Engineering MACE2011, Inner Mongolia.
[4] Yanling Xu, Huanwei Yu, Jiyong Zhong, Tao Lin, Shanben Chen, "*Real-time seam tracking control technology during welding robot GTAW process based on passive vision sensor* ", Journal of Materials Processing Technology, 2012.

Fig. 1. Experiment system with industrial welding robot and camera.

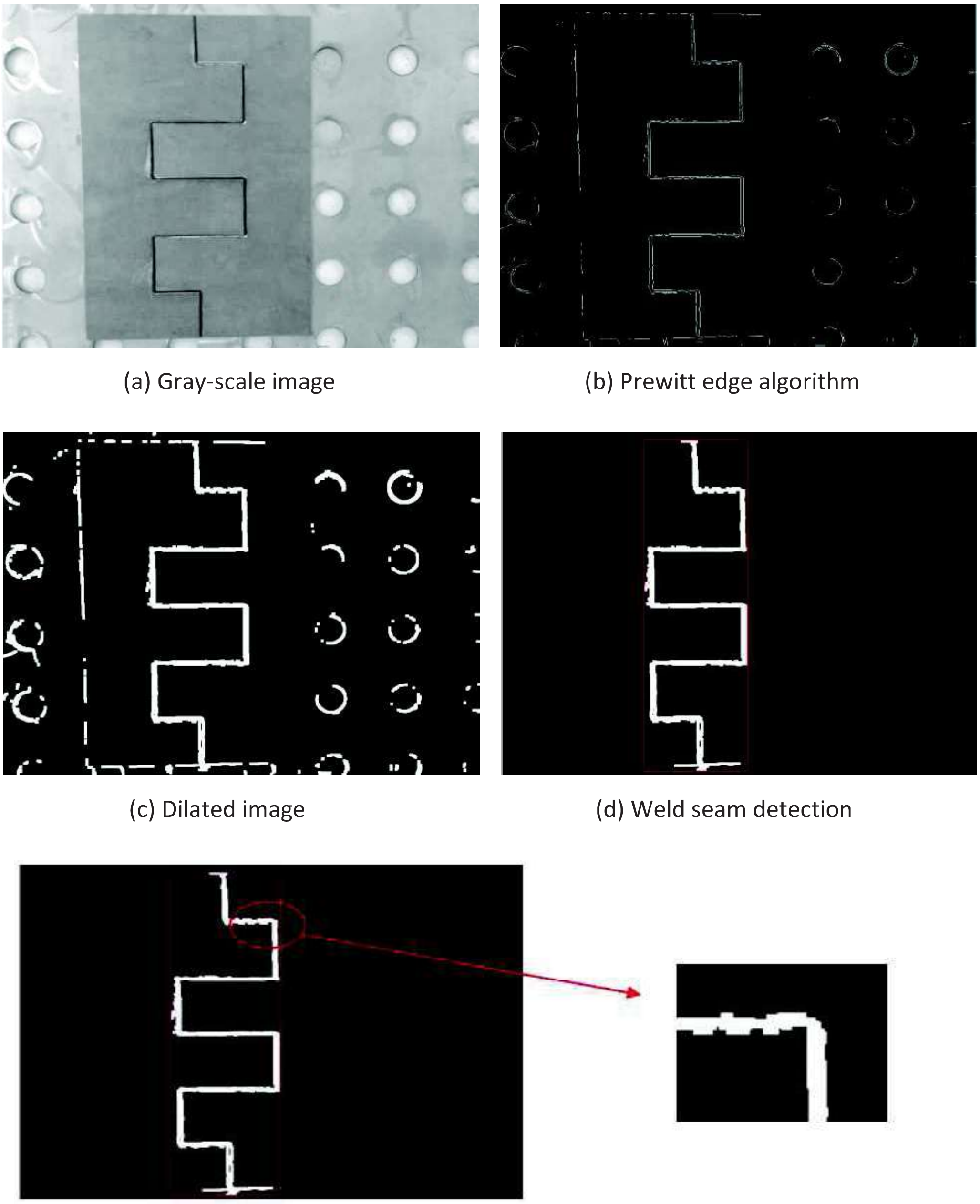
3. Methodology

An overview of the weld seam detection method and image denoising are presented in this section as shown Fig. 2. (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 trainning neural network model. (3) Finally, neural network predictor is generated to remove faults on the resulting image.

3.1 Image capture and seam detection

Firstly, it is captured image of the workpiece on the workbench as shown Fig. 2.a. The captured images are filtered using image processing algorithms via Matlab program for detect weld seam, Fig. 2.b, 2.c, 2.d. Then, obtained images are converted to binary format as shown Fig. 3.

Fig. 2. İmage after image processing filters.



(a) Gray-scale image

(b) Prewitt edge algorithm

(c) Dilated image

(d) Weld seam detection

(e) Faults on the detected weld seam

3.2 Image trimming and convert to binary form

In this experimental study, 1024 x 576 resolution images were captured. A neural network predictor is generated for remove faults on this captured images. The image is converted to a binary image for use as the inputs of the neural network model. The images obtained in the experimental study are large-sized, in order to train to neural network model, the image parts are taken in small-sized and minimized to 23x23 sizes matrix, as shown Fig. 3.

Fig. 3. Convert image to binary image.

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	0	0	0	0
1	1	0	0	1	1	1	0	0	1	1	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0

(a) Trimmed image (b) Converted to binary and 23x23 size image

This resulting image needs to be converted to a one-dimensional matrix in order to be used as an input in a neural network model. For this reason, a 23x23 matrix is transformed into a 529x1 matrix. This matrix obtained is used as training data that has 529 inputs. The neural network predictor is trained with 10 training data from different regions of the main image obtained like this. Then, the results obtained with the test images entered into this trained model were compared.

3.3 Use of the neural network for image denoising

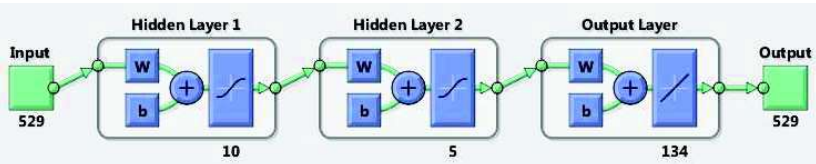
ANNs are frequently used in artificial intelligence applications and produce effective results in the resolution of complex problems. In this study, an ANNs model was developed that is capable of adapting and learning the relation in the sample set and applying it to new input characters. This model should be able to focus on the characteristics of any input that resembles the prevailing shapes, like the pixels that are similar to the known characters but distorted by the noise, and should completely ignore the noise[5]. A new feed-forward backprop neural network predictor has been developed to eliminate the mistakes in the weld seam images obtained with this idea. Fig. 4. This neural network model was trained with 2 different training algorithms, levenberg-marquardt and conjugate gradient, and the results were compared.

[5] Elmas Ç. 2007, Yapay zeka uygulamaları, Seçkin, Ankara, 167s.

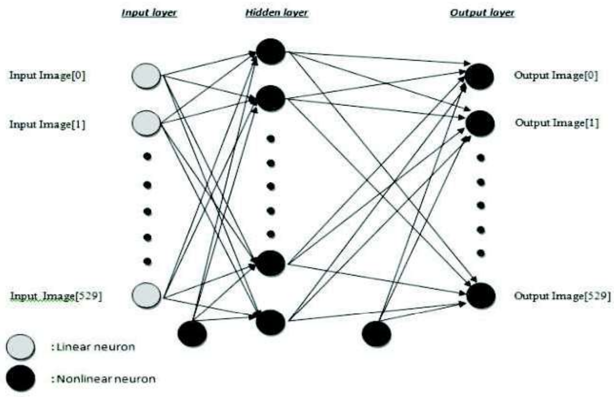
Table 1. Neural network parameters in the study.

NN parameters	*Value*
Max. epoch	2000
Error goal	0.00001
Number of inputs	529
Number of outputs	529
Number of layer	3
Number of neurons in hidden layer	10-5

Fig. 4. Optimal neural network model.



(a) Neural network model for predicting target image.



b) Schematic description of the neural network parameters.

3.3.1 Levenberg-Marquardt algorithm

The levenberg-marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as

$$H = J^T J \quad (1)$$

and the gradient can be computed as

$$g = J^T e \quad (2)$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix[6] . This result obtained using this learning algorithm, which is established according to the parameters in Table 1, is as shown Fig. 5.

Fig. 5. The image denoising using levenberg-marquardt algorithm.

3.3.2 Scaled conjugate gradient algorithm

The scaled conjugate gradient algorithm is based on conjugate directions, as in traincgp, traincgf, and traincgb, but this algorithm does not perform a line search at each iteration[7] . The Scaled conjugate gradient algorithm is employed in this research to further improve the overall accuracy of the neural network because generally this algorithm could provide more iterations than the levenberg-marquardt algorithm. The training of the neural network using an scaled conjugate gradient algorithm was implemented according to the procedure proposed in Section 3.3. The network parameters setup for the training is shown in Table 1. Obtained results are promising, as shown Fig 6.

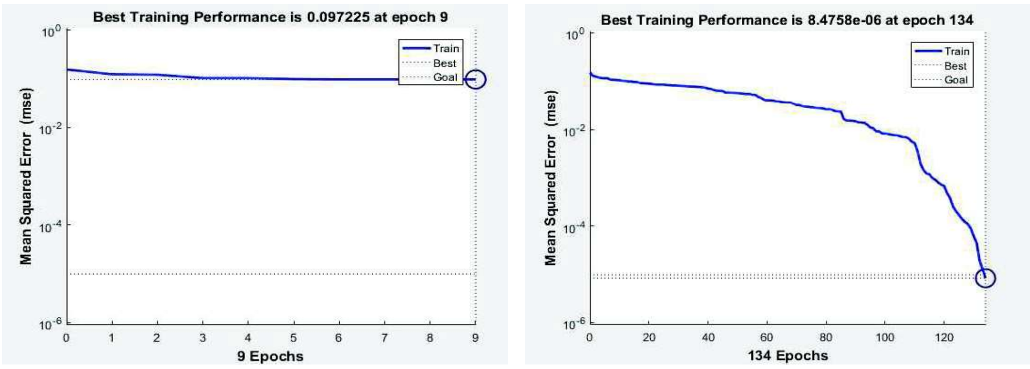
[6] Matworks trainlm function-(web). <https://www.mathworks.com/help/nnet/ref/trainlm.html>. 2017 [accessed 20.01.2017].
[7] Matworks trainscg function-(web).<https://www.mathworks.com/help/nnet/ref/trainlm.html>. 2017 [accessed 20.01.2017].

Fig. 6. The image denoising using scaled conjugate gradient algorithm.

4. Results

In this study, the levenberg–marquardt algorithm and the scaled conjugate gradient algorithm has been used to train the neural network. The obtained results for both algorithms for each case study are shown in Fig. 7. The results in Table 2 show that image accuracy rate, between target image and obtained images from two different algorithm has good performance for predicting this kind of applications in real time. The proposed SCG algorithm has superior performance rather than the L-M algorithm as shown in Fig 7(a)-(b).

Fig. 7. Performance graphics of the two different training algorithm.



(a) The L-M algorithm performance (b) The SCG algorithm performance

The results in Table 2 show that image accuracy rate, between target image and obtained images from two different algorithm....

Table 2. Neural network parameters in the study.

NN parameters	*NN Type*	*Value*
Mean squared error	L-M	0.097225
Mean squared error	SCG	8.4758e-06
Pixel resemblance between images	L-M	% 91,021
Pixel resemblance between images	SCG	% 99,760

5. Conclusion

In this paper, a new approach for image denoising is presented for autonomous weld seam detection. For this intention, neural network predictor is used to determine weld seam on the captured images. Therefore, two different training algorithms are tried. The scaled conjugate gradient training algorithm is used to achieve successful results for train neural network model. The new proposed method improved that a new approach for image denoising using neural network predictor for autonomous detection weld seam.

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[6] Matworks trainlm function-(web). <https://www.mathworks.com/help/nnet/ref/trainlm.html>. 2017 [accessed 20.01.2017].

[7] Matworks trainscg function-(web).<https://www.mathworks.com/help/nnet/ref/trainlm.html>. 2017 [accessed 20.01.2017].