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Detection of Defects on Single-Bead Welding by Machine Learning Methods

Mucahid Barstugan[1,*], Yavuz Selim Ceran[2], Musa Yilmaz[2], Niyazi Adem Dundar[2]

[1]Electric and Electronics Engineering Department, Engineering and Natural Sciences Faculty, Konya Technical University
[2]R&D Center, Hürsan Hydraulic Press and Machine Tools Industry and Trade Inc. Konya, Turkey

*mbarstugan@ktun.edu.tr

Abstract. This study classified the defects that were encountered on single-bead welding, which was made by MIG/MAG welding machines in Hürsan Press company. 2250 images were taken on weldings that were made by five different welders. This study classified defects into three classes as good welding, porosity, and discontinuities. The images in the dataset, which have three classes, were classified by two stages. In the first stage, the texture features of the welding area were extracted. In the second stage, Artificial Neural Networks (ANN) method classified the extracted features. Sensitivity, specificity, accuracy, precision, and F-score metrics were used to measure the classification performance. 1500 images were used to train the system and training and validation performances were obtained as 94.03% and 94.19%, respectively. 750 images were used to test the performance of the proposed method and the test performance was obtained as 94.31%. The proposed method detected a defect on single-bead welding in 0.98 seconds.

1. Introduction

The manual process of welding has more defects than automatic welding. The defect occurrence probability changes according to the ability of the welder. The welding defects are detected by Non-destructive Testing (NDT) experts under enough light. Therefore, there is a probability of a wrong decision on the type of defect during the check process. The aim of this study is to assist NDT experts during welding check process. Also, there are some studies in the literature where machine vision methods were used to detect the welding defects to help NDT experts:

[1] applied Discrete Wavelet Transform (DWT) on friction stir welding images and extracted the texture features. They classified the extracted features with Support Vector Machines (SVM) method and obtained 97% classification performance. In [2], surface defects were defined by image processing methods on friction stir welding images. Five different classes as voids, grooves, cracks, key-hole, and flash were used. [3] classified three different defect types as good welds, excess welds, and insufficient welds. During the classification process, the texture features were extracted by Gray-level Co-occurrence Matrix (GLCM) method. SVM method classified the extracted method. They used only 45 images and achieved 94.45% test performance. [4] detected the welding defects on Radiographic Testing (RT) images. They extracted the texture features on defects by Principal Component Analysis (PCA) method and classified the features with Linear Discriminant Analysis (LDA) technique. They classified 174 images into five different classes and achieved 91.12% classification performance. [5]

classified 1761 RT images into three classes as lack of penetration, incomplete fusion, and external undercut by k-Nearest Neighbor (kNN) and SVM methods. The best classification performance was obtained on lack of penetration defect as 98.03%.
This study has a dataset that consists of three classes, which have 2250 images in total. The texture feature extraction process was implemented by Grey-Level Co-occurrence Matrix (GLCM) [6], Discrete Wavelet Transform (DWT) [7], and Grey-Level Size Zone Matrix (GLSZM) [8] methods and different feature types were extracted. The extracted features were combined and a feature set that represents the image was created. The feature sets of all images were classified by ANN [9] technique.
This paper has four parts. In the second part, the images and features are explained. The third part presents the classification results. The fourth part evaluates the results and discusses future studies.

2. Material and Method

The images in this study were taken on welding that was made by different synergistic welding machines in Hürsan Press Company. The images were taken under three different environments as the dark environment, daylight, and factory environment. Three types of defects, which were made by five different welders, were photographed in three different environments to increase the reliability of the proposed method. Because of five different welders, the dataset has data diversity. The images were taken with 3 mega-pixels snake camera, which is positioned with a right angle, from a 3cm distance. The images were obtained with 640x480 dimensions. The snake camera has six LEDs around itself to provide a high light on welding. NDT experts also use high white light to evaluate the type of defects. Figure 1 shows the welding in the factory environment and the apparatus, which was used to take photographs.

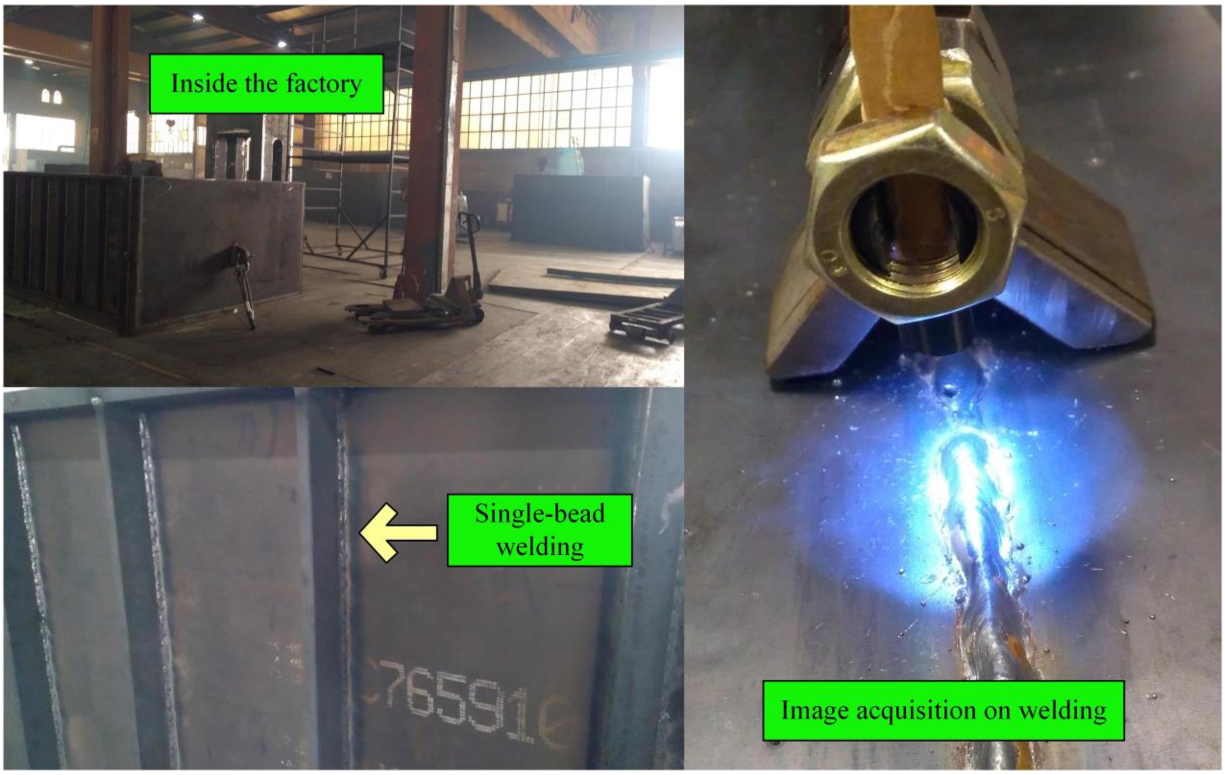

Figure 1. Factory environment and the apparatus used.

Figure 2 shows the sample images after image acquisition.

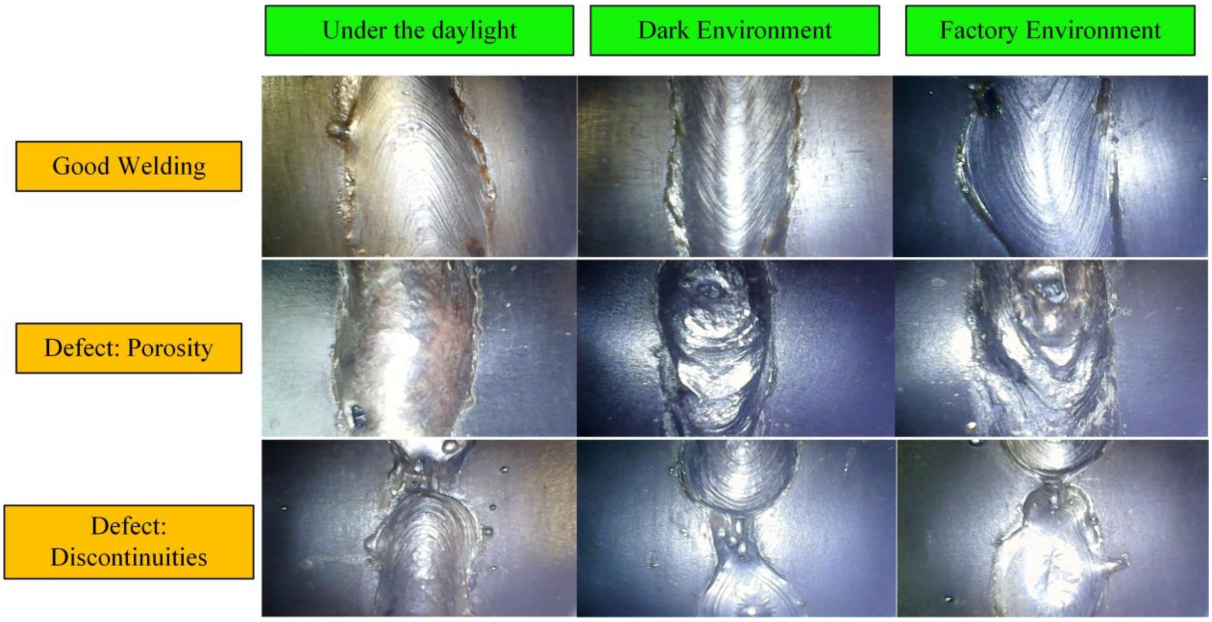

Figure 2. The images in the dataset that have different types of defects.

As shown in figure 2, all of the weldings were taken under different environments. All LEDs on the snake camera were used in full power in all environments during image acquisition. The reason is that NDT experts check the welding under high white light. Figure 2 shows the porosity defect, which is caused by insufficient protection and dirty workpieces. Discontinuities defects occur according to the ability of welder and whether the speed of wire riding is fast or slow. This study proposes a method to classify the welding defects automatically. In the proposed method, the defects are classified by artificial intelligence methods. The proposed method extracts the texture features on welding by GLCM, GLSZM, and DWT techniques. Then, the extracted features were used to train the ANN classifier. The scheme of the proposed method is presented in figure 3.

Figure 3. The scheme of the proposed method.

During the feature extraction process, 19, 13, and 24 features were extracted by GLCM, GLSZM, and DWT (db1 wavelet is used) methods, respectively. In the DWT method, the mean, standard variation, energy, entropy, skewness, and kurtosis features were obtained on four result images. All extracted features were combined and a feature set, which has 56 features, was obtained for one image. The system was trained with 56 features for each image.

3. Experimental Results

This section presents the classification results. During the classification stage, three different parameters in the ANN method were changed to evaluate the classification results. The learning rate (LR) parameter was changed between 0.1~1 (step by 0.1) and 2~10 (step by 1). The number of iteration (NoI) was changed between 5000~20000 (step by 1000), and the number of hidden neurons (NoHN) was taken as 6, 13, and 27. Three hidden layers were used in the neural network structure. Purelin and traingdx functions were used as activation and training functions, respectively. There could be an infinite number of experiments in the ANN structure; therefore, the experiments were implemented between the intervals given above. The neural network, which gave the best classification performance, was saved to use during the test stage.

The dataset has 750 images for each class. 500 and 250 images were used for training and test stage, respectively. During the training stage, the network was trained with 10-fold cross-validation method and tested by training and validation dataset, which were automatically created during the 10-fold cross-validation method. The network, which gives higher classification accuracy on validation dataset than training dataset, was saved. This provided to prevent the overfitting situation in the network. That means the network learned the dataset, did not memorize. The networks, which have higher validation performance, were used in the test stage and the obtained test performances were compared. The detailed scheme of the training and test stages are presented in figure 4. The best classification results and the parameters are presented in table 1.

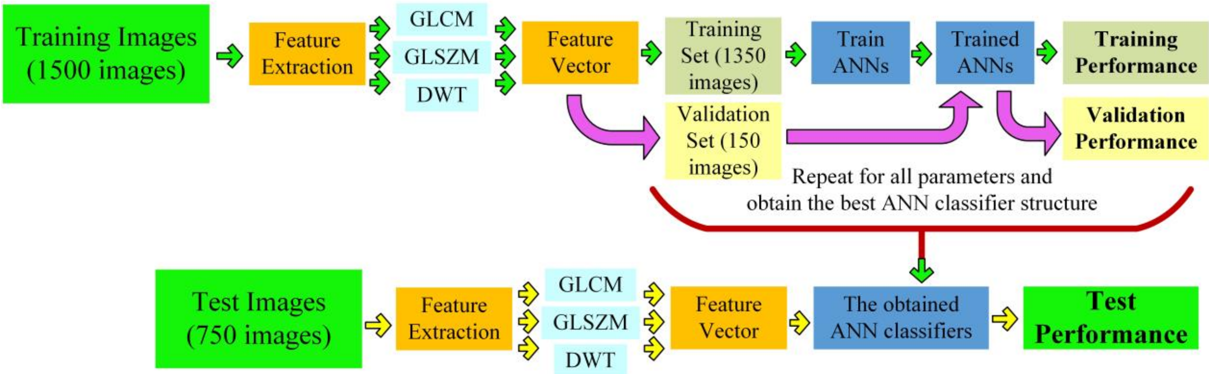

Figure 4. The detailed scheme of the training and test stages.

Table 1. The classification results for different ANN parameters.

Neural Network	Data	Evaluation Metrics (%)					ANN Parameters		
		SEN	SPE	ACC	PRE	F-score	NoHN	NoI	LR
Network 1	Training	90.47	95.11	93.48	91.08	90.60	56/**6**/3	11000	5
	Validation	90.60	95.16	93.56	91.16	90.69			
	Test	83.6	99.14	93.72	98.12	90.28			
Network 2	Training	91.24	95.54	94.03	91.82	91.36	56/**13**/3	16000	1
	Validation	91.47	95.67	94.19	92.17	91.57			
	Test	**85.2**	**99.15**	**94.31**	**98.16**	**91.22**			
Network 3	Training	88.53	94.11	92.11	89.44	88.71	56/**27**/3	9000	2
	Validation	88.87	94.31	92.36	90.04	89.04			
	Test	83.20	99.58	93.89	99.05	90.43			
Network 4	Training	90.21	95	93.30	90.91	90.35	56/**27**/3	20000	0.2
	Validation	90.27	95.03	93.35	91.05	90.40			
	Test	82.8	99.36	93.58	98.57	90			

Table 1 shows that the best test performance was obtained with Network 2 as 94.31%. Other networks also gave promising classification results in the proposed method.

4. Conclusions and Discussions

This study classified the welding images with high performance. The images of different weldings were taken in different environments to increase the reliability of the proposed method. The training duration of the ANN structure was obtained as 282 seconds, while the test duration was obtained as 0.98 seconds only. This shows that the proposed method detects the type of defect in shorter than one second.

As mentioned in the experimental results section, there could be done an infinite number of experiments to find the optimum classifier parameters. This study chose a specific interval for three different parameters and obtained the results.

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Future studies will focus on classifying six different defect types. A smart system will be created to detect the defect with a high classification performance. The smart system will be implemented on hardware to use in Hürsan Press Company to help the NDT experts during the check process.

5. References

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