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Development of welding discontinuity identification system using statistical texture feature extraction and ANN classification on digital radiographic image

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A B S T R A C T

Discontinuity in welds is one of the causes of the quality of a connection in the material decreases function. Undamaged test with radiographic method is one of the tests to see the quality of a weld. The test results are radiograph images and evaluated by a radiographer. So this research is designed by optimizing a system to help the work of a radiography expert in identifying discontinuities by utilizing the Matlab Application. On this system uses the method of characteristic extraction and classification of neural networks (ANN). The system uses a characteristic extraction method with geometric invariant moment (GIM) algorithms and a gray level co-occurrence matrix (GLCM) as identification values used in the classification process. The classification process uses a backpropagation-type multilayer Artificial Neural Network. The types of discontinuities used as data in this system are incompleteness of penetration, crack, wormhole, and distributed porosity using a total of 800 datasets of radiograph imagery data. This data sharing is organized using k fold cross validation. The study conducted 15 experiments in system testing to prove the truth in identifying. The results of the experiment resulted in the highest average performance score reaching 93.33%

Introduction

Inspection of the weld structure is very important to ensure that the quality of the weld meets the requirements for both design and operation, therefore to ensure safety and reliability, inspections are carried out using the Non Destructive Test (NDT)

method. NDT inspection is an activity to uncover or detect all types of damage on the surface of objects or inside the object such as cracks, porosity, and various other types of damage [1].

The NDT inspection method used is radiography because this method utilizes X-

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rays and gamma rays which are able to penetrate almost all metals so that they can be used to reveal discontinuities or discrepancies behind metal walls or within the test object material itself [2]. The radiographic image must be evaluated to see the quality of the weld based on the resulting image. Identification of weld discontinuities contained in radiographic images can only be done by someone who has special abilities or competencies as evidenced by a Radiography Expert certificate of competence. The evaluation process is manual so it takes more time. The process of identifying defects has the potential to experience identification errors because it is very much determined by the subjectivity of AR. Therefore, we need a system that can help AR work in identifying weld discontinuities on digital radiographic images automatically [3].

Weld discontinuity identification system on digital radiographic images was developed by applying the combination of segmentation, feature extraction, and classification techniques. The current segmentation technique is not able to separate the weld discontinuities from the intact radiographic film image. The feature extraction technique uses a lot of geometric measurement techniques that are very dependent on the shape of the discontinuity. Then, the various classifications used have not utilized the stochastic approach as used in conventional interpretation [4].

In a previous study conducted by Agus Probo Sutejo with the title "identification of welding defects with geometric invariant moment on digital radiographic images" (2020) regarding the manufacture of an automatic welding discontinuity identification system in evaluating radiographic images (Sutejo, 2020). In the research and the system that has been made, it has not been able to detect more than one discontinuity in one radiographic image. Therefore, a research was conducted on the development of a welding discontinuity identification system in order to assist radiographers when

evaluating radiographic images, adding types of discontinuities for identification, as well as readings made by a documented computer system. Thus, this research can be used as a tool to identify weld discontinuities automatically.

Methods

The radiographic image used as data in the identification system comes from two types of data, namely secondary data and primary data. The secondary data was obtained from the IIW (International Institute of Welding) version of radiographic film data, and the primary data was obtained from the results of radiographic testing of standard materials using a Detector Direct Radiography that had been interpreted. The radiographic image used has an indication of weld discontinuity, including Distributed Porosity, Crack, Wormhole and incomplete penetration.

Making the system in this study using the Matlab application which incorporates several programs including an image processing preparation program or preprocessing, geometric texture feature extraction algorithm and ANN classification to identify weld discontinuities in digital radiographic images automatically [5]. In general, the working principle of the identification system is that the radiographic image will be cut according to the position of the discontinuity, then the cropped image will be automatically converted into an image that has a gray value or called grayscale, then the image will be extracted features with a geometric invariant moment algorithm and combined with the Gray Level Co-occurrence Matrix algorithm [6]. The value of the feature extraction process will be used as classification class data in the artificial neural network classification algorithm. This classification process will compare the value of the incoming image feature extraction with a feature extraction dataset that has a feature extraction value close to the same. The results of the classification process will be displayed on

the user's GUI by displaying the definition of the classified weld discontinuity [7]. The following is a flow diagram in making the identification system as shown in Figure 1.

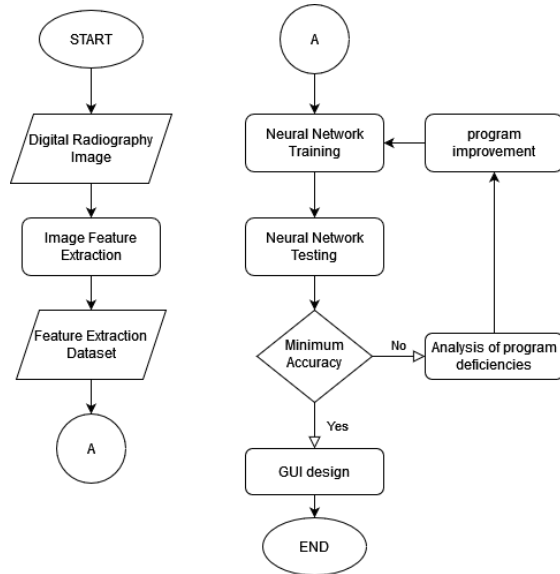


Figure 1. Flowchart of the identification system making process

Based on the flow chart, the discontinuity identification system is made using digital radiographic images obtained from material testing. The radiographic image data that has been prepared will go through the image preprocessing stage before being processed into data in the identification system.

1. Radiographic Image Processing

Digital images are arranged in the form of a grid. Each square is called a pixel and has coordinates (x,y) is $f(x,y)$. The x-axis is the row, while the y-axis is the column. Each pixel has a value that indicates the color intensity of that pixel. Figure 2 is an example of a digital radiographic image.



Figure 2. Radiographic image

Radiographic image processing is a step to obtain information from an image that will be used as input data in the identification system. The initial stage in processing radiographic images is called preprocessing. At the preprocessing stage, it

consists of converting the image into gray scale (Gray Scale) and cutting the image[8]. The image conversion stage is the process of changing the radiographic image into a grayscale image. The converted image will then be cut according to the discontinuity position. The cut point size is 370 x 150.

2. Extraction of Geometric Invariant Moment (GIM) and Gray Level Co-occurrence Matrix (GLCM) features on radiographic images

GIM feature extraction will produce 7 moment invariant values in each image, so that the output data for this feature extraction is a matrix measuring 7 x 400. 7 values of invariant moments are obtained by deriving the second and third moment equations for the second and third sequence moments [9].

$$\emptyset_1 = \mu_{20} + \mu_{02} \quad (1)$$

$$\emptyset_2 = (\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2 \quad (2)$$

$$\emptyset_3 = (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2 \quad (3)$$

$$\emptyset_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2 \quad (4)$$

$$\emptyset_5 = (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12})$$

$$\left((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2 \right) + (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2) \quad (5)$$

$$\emptyset_6 = (\mu_{20} - \mu_{02}) \left((\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2 \right) + 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03}) \quad (6)$$

$$\emptyset_7 = (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12}) \left((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2 \right) - (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2) \quad (7)$$

This 7 x 400 matrix is a matrix for all types of weld discontinuities. Gray Level Co-occurrences Matrix (GLCM) is a matrix that is formed according to the relationship between one pixel and another pixel in the image. Extraction using the GLCM method produces four characteristic values, namely Contrast, Energy, Homogeneity, and

Correlation. GLCM can work with changes in geometric operations (rotation, scaling, and translation), because the dependence of values between pixels depends on the angle and distance of the environment. This allows GLCM textures to be used as image descriptors [10].

The GLCM feature extraction information is simply determined by the relative frequency matrix $P(i,j)$ where two adjacent resolution units appear to be separated by a distance d in the image, and one has a gray value of i , and the other has a gray value of j . This spatially related gray tone frequency matrix is a function of the angular relationship between adjacent units of resolution and the distance between them. Figure 2. Shows a group of all horizontally adjacent resolution units with a distance of one between them. This unit is used in conjunction with the image grayscale to calculate the spatial correlation matrix of interval 1 of the horizontal grayscale. Formally, for the maximum angle measured is 45° , the non-normalized frequency intervals are defined as $0^\circ, 90^\circ, 45^\circ, 135^\circ$ as in Figure 3 [11].

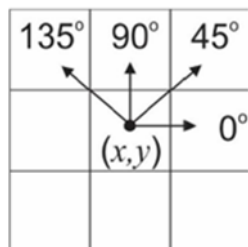


Figure 3. GLCM matrix with directions $0^\circ, 45^\circ, 90^\circ, 135^\circ$, and distance d 1 pixel [12]

This study uses four feature values to be applied, namely entropy (f_E), contrast (f_C), moment of both angles (f_A), and moment of inverse difference (f_I). This feature value will be formulated in equation (8 - 11), where $p(i,j)$ is a normalized co-occurrences matrix.

$$f_E = -\sum_i \sum_j p(i,j) \log p(i,j) \quad (8)$$

$$f_C = -\sum_i \sum_j (i-j)^2 p(i,j) \quad (9)$$

$$f_A = -\sum_i \sum_j (p(i,j))^2 \quad (10)$$

$$f_I = -\sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \quad (11)$$

The results of the GLCM feature extraction are used for direction orientation, so that the output data for this feature extraction is a matrix measuring 4×400 . This matrix with a size of 4×400 is a matrix for all types of weld discontinuities.

3. Image feature extraction dataset

All feature extraction images produce a matrix which is known as a feature dataset. The image feature extraction matrix will be labeled according to the type of discontinuity. Then the dataset will be divided into two parts, namely the training dataset and the test dataset to be used in the classification of Artificial Neural Networks.

The artificial neural network training process aims to implement and produce an artificial neural network model with the expected accuracy value achieved during testing. The artificial neural network classification model used in this study is backpropagation pattern recognition. In the training process with the artificial neural network training algorithm, a dialog window will appear as shown in Figure 4.



Figure 4. Training Process

If the expected accuracy value does not meet the target, then carry out the evaluation process of the artificial neural network by re-training the artificial neural

network. Until the accuracy value is met. The results of the artificial neural network training are then tested with a test dataset to determine the accuracy value of the artificial neural network model used. The identification system that has been created is carried out at the testing stage on digital radiographic images. The success parameter of the identification system is that the system can describe the type of weld discontinuity in the digital radiograph image.

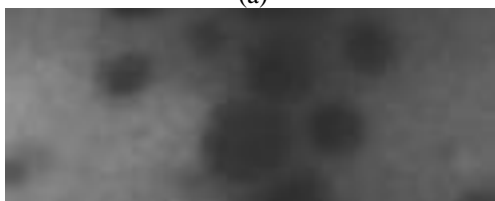
The test carried out is making the system by designing a Graphical User Interface (GUI). The purpose of designing a GUI is to show the work process of the system that has been made during research to users to make it more practical to use.

Results and Discussion

The results of image data retrieval used as input data for the discontinuity identification system in the form of 2D images obtained from standard IIW films and standard material testing with stainless steel materials with known types of weld discontinuities. The digital image that has been obtained is then cut into a cutting process so that an image with a size of 300x100 is obtained as shown in Figure 5.



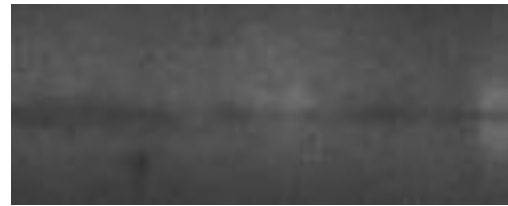
(a)



(b)



(c)



(d)

Figure 5. IIW standard film (a) Crack Discontinuity, (b) Distributed Porosity Discontinuity, (c) Wormhole Discontinuity, (d) Incomplete Penetration Discontinuity

Table 1. Feature extraction value

Description	Crack	Porosity	Wormhole	IP
<i>Contrast</i>	0.128	0.078	0.034	0.135
<i>Correlation</i>	0.928	0.956	0.538	0.854
<i>Energy</i>	0.222	0.254	0.894	0.334
<i>Homogeneity</i>	0.936	0.961	0.983	0.933
Ø1	7.539	7.286	6.663	7.378
Ø2	11.332	11.650	10.999	12.265
Ø3	21.574	24.524	23.338	25.857
Ø4	21.532	24.387	23.242	25.644
Ø5	43.107	49.434	46.551	51.395
Ø6	27.199	30.425	28.751	31.782
Ø7	44.576	49.555	48.722	56.706

In this study, an identification system was created to identify or classify digital radiographic images, to determine the level of accuracy of the designed artificial neural network, it is necessary to test the introduction of several new image samples. The test does not include samples that have been trained in ANN, this is because the accuracy of using training data reaches 100% which provides associative input and the target is perfect. ANN is made by doing learning based on a model (learning by example), where the intended example is a sample that is trained into the network. by testing samples that have been trained in ANN, the accuracy rate will reach 99.7% and is in accordance with what is obtained. In this test, it must be ensured that the type of weld discontinuity to be tested has a similar feature extraction pattern using the feature extraction pattern that has been stored in the database, namely porosity, crack, wormhole, and incomplete penetration weld discontinuity patterns.

The image sample used as a database has a feature extraction pattern similar to one type of discontinuity because each type of weld discontinuity has a typical GIM and GLCM feature extraction value. With a

pattern of similar characteristic values, the network convergence process towards the desired target matrix is fast. if the spectrum pattern of the new sample to be tested has a pattern that is not in harmony using the database, it is possible that the recognition results will be wrong.



Figure 6. The configuration of the artificial neural network

Figure 6 is a configuration of the artificial neural network model that has been made with the specifications as listed in Table 2.

Table 2. Parameters number

No.	Parameter	Parameter Number
1.	Input	11
2.	Layer	3
3.	Output	1
4.	Hidden layer transfer function	Tansig
5.	Output layer transfer function	Purelin
6.	Training Type	Trainlm
7.	Epoch	1000
8.	Minimum gradient	1.00e+10

The configuration of the artificial neural network model used is the backpropagation neural network model. The backpropagation type of artificial neural network model is an artificial neural network method that uses multilayer perceptions to classify complex problems. Backpropagation also performs back calculations from the output neurons so that they have the appropriate weight values in the artificial neural network. Therefore, this study uses a backpropagation-type artificial neural network model so that the error value of the discontinuity classification process in this study can be reduced quite well. In the training of artificial neural networks in this study, the error value was minimal. The following graph shows the training error of the artificial neural network in Figure 7.

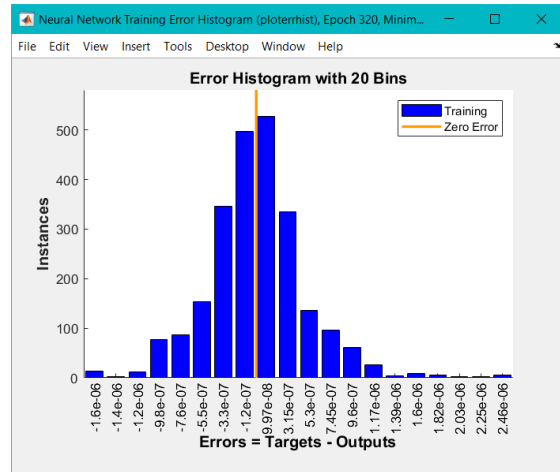


Figure 7. Error histogram of artificial neural network training

After the two stages are completed, the merging process is carried out into one command. The combination of these commands generates an identification system and displays it on the interface, a graphical user interface. The GUI is used to display the final results of the production recognition system, and is also convenient for users to use.

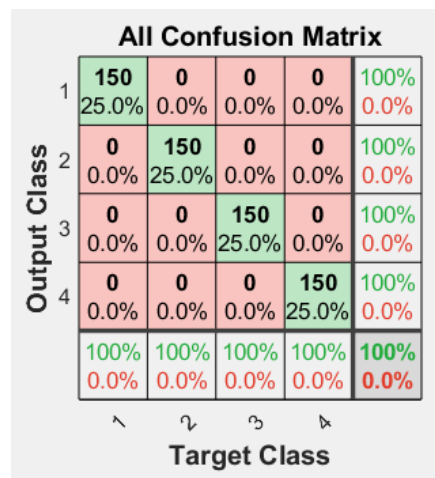


Figure 8. Confusion Matrix training of artificial neural networks

The figure shows that the simulation program performs tests by recognizing as many as 15 radiographic image samples of each type of discontinuity in each test. In the test, each type of discontinuity can identify 14 images correctly, while 1 sample of radiographic images can identify discontinuities incorrectly. Based on the feature extraction value pattern of the tested radiographic image sample, it is almost the

same as the extraction value pattern contained in the database. so that the artificial neural network cannot recognize the type of discontinuity, but instead becomes the value of the type of discontinuity whose pattern of extraction values resembles other discontinuities. From the test, the accuracy obtained is 93.33%.

Conclusion

Weld discontinuity identification system on digital radiographic image using GIM feature extraction method and ANN classification has been successfully developed. The identification system that has been made has not yet obtained the expected accuracy value with a minimum value of 93.33% so that the identification system program cannot be tested using the GUI.

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