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Research Article

Non Destructive Evaluation of Welded Joints in Hermal Bands Using Neural Networks

Akshatha Aravind[1] and Arun VA[2]

[1]*Department of Electronics and Communication, KR Gouri Amma College of Engineering, Cherthala, Alappuzha, Kerala, India*

[2]*Department of QA and QC, Nesma and Partners, Damam, Saudi Arabia*

***Corresponding Author:** Akshatha Aravind, Department of Electronics and Communication, KR Gouri Amma College of Engineering, Cherthala, Alappuzha, Kerala, India.

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Abstract

Thermal imaging is simply the technique of using the heat given off by an object to produce an image of it or locate it. Several thermal imaging frameworks for the detection of defects in welded joints have been introduced in literature. Weld joints are the origin of structural weakness in maximum cases and must be routinely inspected to ensure structural integrity of the fabricated components. Hence the defect detection on welded joints has become a significant task, as it provides the fundamental information for semantic understanding of the scene. This research aims to develop a specialized algorithm that would use the defect's heat signature for detection, density of defect and applications that takes benefit of this technology. The algorithm is mainly divided into several segments which go like object capturing, Temperature decay variation, filtering, validation etc. It may embed a module for the automatic determination of the range of defect temperature variation using the learn and adapt technology of neurons. This technology surpasses previous approaches like Edge detectors, morphological operators, finding interest points and region of interest, features matching. Certainly, the research outperforms the result obtained by visible images with the boon of most advanced non visible spectrum thermal cameras.

Keywords: Thermal Image; Non - Destructive Evaluation; Infrared Thermography; Adaptive Neural Network

Introduction

To fabricate the complicated or huge industrial component the welding plays an important role. The expense in manufacturing complex components in industries is high. Thus design, fabrication and inspection of the welding joints are a major step. The main failure occurs at the weld and heat affected zone of the material. Commonly the failure are caused due to the improper design of the welding processes, selection of base materials and filler materials, residual stresses, inspection procedures, operating parameters and weld joints. To minimize the failure in the welding parts non destructive testing (NDT) can be employed. Few basic NDT methods such as penetrate, ultrasonic, radiography, visual testing are sufficient and routinely employed for the inspection of welds, use of advanced NDT techniques is resorted to when high sensitivity detection and quantitative characterization of harmful defects is envisaged.

In order to maintain proper operation of a structure or a component in-service degradation and pre-service quality of the component should be in a working condition. Non-destructive evaluation (NDE) is the technology used to monitor the in-service condition of the component and also it is used to establish the pre-service quality of the structure or component. Thus NDE is the process used to find the defect in the structure or component. It can also be stated as NDE is used to evaluate the identify parameters like micro-structural degradations, defect, stresses of the materials. This is accomplished by making correlation between the non-destructive measured derived/physical parameters and useful information related to the stresses, micro-structures, defects. Thus the quality of the component or structure can be evaluated by taking the information obtained from NDE and design parameters.

NDT procedures

- Immediately after the fabrication to make sure the welded joint is defect-free
- During the service life of welded components to ensure that no unacceptable defects are present and grow [1].

The six most frequently used NDT methods are liquid penetrate, eddy-current, magnetic particle, visual testing, radiographic and ultrasonic. NDT is commonly used in forensic engineering, mechanical engineering, petroleum engineering, electrical engineering, civil engineering, systems engineering, aeronautical engineering, medicine, and art.

In thermal image processing the infrared radiation or heat is converted into visible images. The emitted infrared energy of the object is known as the heat signature. Commonly the radiation generated by the hot object is more as compared to the object with normal temperature. Infrared thermography (IRT) analyse the thermal information of an object with the help of a non contact thermal imaging devices. IRT is deployed along two schemes, passive and active. The passive scheme tests materials and structures which are naturally at different (often higher) temperature than ambient while in the case of the active scheme, an external stimulus is necessary to induce relevant thermal contrasts (which are not available otherwise, e.g. specimen at uniform temperature prior to testing). Thus IRT is a technology that can instantly visualize and verify the thermal performance.

IRT is secured processes as there is no harmful radiations are exhausted or high power external simulations are not used. In IRT process there is an increased inspection rate. Using IRT it is easy to make images formation or easy to interpret the images of the object. IRT can generate the image of large surface area in short time period thus less time consuming.

The result can be generated in visual and digital format. The IRT use high quality and performances instruments to detect the defect the cost of instrument are high. Also it is not able to detect the defect inside temperature if the object is separated by glass or a polythenematerial. IRT are commonly used in the areas like medical imaging, night vision, condition monitoring, and process control chemical imaging non-destructive testing.

The use of computational tools for pattern recognition, as artificial neural networks (ANN), offered a new way to classify the defects detected by the ultrasonic technique. The heat propagated from active scheme which can damage the welding joints, then to identify the defect ANN or pattern recognition technique is used. The defects that are identified by the NDT should be recognized or classified. For the classification of the defect the most advanced method called artificial neural network (ANN) is used.

The increased application of ANN in industrial field is due to its high performance and the performance accuracy. In the analysis process after processing mechanical property of the material using the variable applies. After that the detection of the defects or irregularity of the material and machine tool positions are identified. It also identifies the wear in the tool. Then the defect is evaluated using the NDT.

This paper is organized as follows: The major defect in the welding point is briefly discussed in Section II. Section III and section Feature Extraction and presents idea of ANN applies in weld defects detection and section IV gives the concluding remarks.

Detection of detects in welding

The common two methods used to detect the defect in welding joints are destructive Test (DT) and non destructive Test (NDT). Metallogrphic test is a type of DT, which is proposed by Victor., *et al.* [2]. The method is used commonly used for test the section cut the weld bead part in wanted plane. But the integrity and original shape of the weld bead is not maintained for a long duration in this testing.

Normally for NDE weld defect detection, bare human eye is the used and for the recording the result the non-destructive testing is used [3]. In industrial application also NDT test like visual inspection (VI), inspection liquid penetrant (ILP), magnetic particle inspection (MPI), ultrasonic, acoustic emission (AE), radiography and Eddy current are accepted. VI, ILP and MPI are based on eye inspection only. But for radiography, acoustic emission and Eddy current the output should be monitored in digital image or analog wave signal.

Weld defect classes into eight types. Still, defects finding and visual appearance limit certain test to detect some defects. For instance, crack is commonly present in sub surface area of weld bead. Plus various views of check such as the inspection of undercut and weld profile defect can only be validated from side view and appearance of incomplete joint penetration defect can be notified from bottom view. These factors make this all type of defects cannot be detected by some test. Test such as ultrasonic, radiography, and Eddy current make those defects possible for detection. Other defect includes inclusions; incomplete fusion, overlap, and porosity are observable via human eye vision. Radiography digital image was studied by different researches and there results are given in the table 1. From the table it is clear that Metallographic testing is the less used for testing.

Ref	Test Method
[2]	Radiographic
[4]	Radiographic
[5]	Radiographic
[6]	Radiographic
[7]	Radiographic
[8]	Time-of-flight diffraction (TOFD) ultrasound wave signal
[9]	(TOFD) ultrasound wave signal
[10]	Radiographic &Eddy Current Signal
[11]	Radiographic
[12]	Radiographic

Table 1: Different test methods.

Features of the detected defect

The feature has domains that can be classified into two, named as spatial and frequency domain. The spatial domain is a feature directly obtains from a recorded data. Frequencies obtained from a digital images or records e.g. pixel intensity; needed to undergoes image processing before generating it features, for instance histogram or profile - frequency domain. Data collected from weld defect tests may come in many form of information. Hence for data applicability, preprocessing operations will lessen information content with the goal to find a subset of informative variables. The operation includes image processing, determining spatial features, and frequency features.

Ref	Accuracy	Parameters
[13]	Weld flaws are classified according to the imbalanced class data (93.5%).	Distance from the weld center, mean radius, standard deviation of radius, circularity, compactness, major axis, width, length, elongation, Heywood diameter, mean intensity and intensity standard deviation
[6]	Radiographic images that are generated automatic system of classification. (Mean of 80.4%)	Area, centroid, major axis, minor axis, equivalent diameter, Euler number, orientation, eccentricity, solidity, extent and position. Input vector is created for each defect and human experts in produce a target vector.
[14]	Using geometric and texture features multiclass defect detection and classification in weld radiographic images. (Around 85%)	A set of eight geometric features: the weld bead relative position, aspect ratio, length/area ratio, area/bounding rectangle ratio, roundness, rectangle ratio, Heywood diameter and weld bead relative angle. Correspond to mean value and standard deviation of the gray level values of all pixels in object the intensity-based descriptors are defined for each segment. Angular second moment, contrast, correlation, sum average, squares sum, difference variance, inverse different moment, difference entropy, entropy, and sum entropy are the texture features that are measured.
[7]	Performance evaluation of an automatic inspection system of weld defects in radiographic images based on neuro classifiers (Mean of 76%)	Area, centroid, major axis, minor axis, eccentricity, orientation, Euler number, equivalent diameter, solidity, extent, and position are the different factors that are measured.

Table 2: Features of the detected defect.

Image processing application

Image processing generated better quality image and yet still preserve the image critical information. Processed digital images are used to extract features of the principle - welding defects features. The processes selection based on preliminary observation and outcome in a study such as: grey scale image provides sufficient amount of information for this study, unavoidable the mixture of quality pixel and noise pixel; separation backward and forward region; need of binary image for image analysis and perform operation on particular region.

Grey scale image conversion discriminates information that are not needed, in this case original image colour of red-green-blue (RGB image). Image originally generated in grey scale no need for this process e.g. radiographic image. Previous researches related to detecting and classification study mostly only considered grey level component as it is effective technique this purpose. [15,16] used this technique in their studied. The grey level value or intensity of noise pixel is much higher than those of their immediate neighbor i.e. Pixels relatively close to refer pixel.

Noise reduction technique with variation of methods applied by [6,14] successfully applied in their research. Noise reduction process will take place for this matter by using for example Low -pass filtering method that employ median filter to set up at a small template. The operation of template will be calculated by correlation operator. The result from correlation operator will be used and replaced noise pixel's grey level with the median value of their neighbourhood. The benefit from this operation is the edges preservation while suppressing noise pixels. Common alternative methods for noise reduction includes Weiner Filter which is a linear estimation of the original image; and Gussian Low-pass filter creates an effect called boundary related ringing in deblurred images. This noise reduced image is then will goes into next process such as image segmentation process. The aim of image segmentation is to transform existing grey level image into binary image.

Artificial neural network

The use of pattern classification initially were often use by linear and quadratic discriminant; nonparametric k-nearest neighbour classifier, decision trees, and Parzan density estimator. Minimum Distance Classifier and Fuzzy-Nearest Neighbour algorithm are used by few applications.

However the best about trained ANN is, it can perform almost any regression or discriminant task. Thus ANN is widely use and a renowned pattern classification method with supervised algorithm to classify weld defects. Besides, Enkhsaikhan, [17] noted of "a properly train ANN can provide better performance than conventional signal [input data] processing method", makes ANN method outperform other alternatives to use for the automation. In 2011, Arulozhi generalized that ANN methodology are (i) create network, (ii) train network, (iii) validate network, and (iv) apply network. Huge amount of iterative work to create network, train network, and validate network required in order to have validated network.

ANN algorithm

The selection of an ANN algorithm is crucial to achieved high accuracy rate. Table 3 shows the trend of researchers use ANN algorithm in weld defect detection. ANN algorithm such as Multilayer Perceptron by [2,18]; Adaptive-Network-Based Fuzzy Inference System (ANFIS) by [6] and Self Organizing Map by [2]; have been tested to detect weld defects. Yet, Feed forward Back propagation is the most popular algorithm by researchers used to detect weld defects. This is due to the algorithm is fast and high percentage of accuracy that can be achieved. Based on record the highest rate at 95% by Senthil Kumar, Natarajan, and Ananthan [16] has been achieved via Feed forward Back propagation algorithm.

Ref	Defect detected	Algorithm
[19]	Multiclass defect detection and classification in weld radiographic images using geometric and texture features	A feedforward ANN of one input layer fed with the set of input variables, one hidden layer of adjustable number of hidden neurons and one output layer of one neuron. The tansig and logsig are used as activation functions in the input and output layer and training with backpropagation.
[18]	Automatic detection of welding defect using radiography with a neural approach.	The automatic control and inspection in welding defects is made by edge detection method of radiographic images, based essentially on the use of Multilayer
[7]	Performance evaluation of an automatic inspection system of weld defects in radiographic images based on neuro-classifiers	Multi-layer feed-forward artificial neural network. Nonlinear pattern classifiers were implemented using ANNs of the supervised type using the error backpropagation algorithm and two layers, one hidden layer (S1 neurons) using hyperbolic. Tangent sigmoid transfer function and one output layer (S2 = 5 neurons) using a linear transfer function.
[14]	Multiclass defect detection and classification in weld radiographic images using geometric and texture features	The neural network used one hidden layer with variable number of neurons, ranging from 4 to 20 and was trained using back-propagation with adaptive learning rate and momentum.
[6]	An adaptive-network based fuzzy inference system for classification of welding defects	An adaptive-network-based fuzzy inference system (ANFIS) to recognize welding defects in radiographic images. This system structurally equivalent to an artificial neural network (ANN) and represents a useful neural network approaches for the solution of these types of problems.
[20]	Spectral processing technique based on feature selection and artificial neural networks for arc welding quality monitoring	The net is a multilayer feed- forward network, and a back-propagation learning algorithm with an adaptive learning rate has been employed. Neurons in all layers have a log-sigmoid transfer function.
[6]	An automatic system of classification of weld defects in radiographic images	Multi-layer feed-forward ANN of the supervised type using the error back-propagation algorithm and two layers, one hidden layer (S1 neurons) using hyperbolic tangent sigmoid transfer function and one output layer (S2 ¼ 5 neurons) using a linear transfer function.
[2]	Evaluation of multilayer perceptron and self organizing map neural network topologies applied on microstructure segmentation from metallographic images	A comparative analysis between multilayer perceptron and self- organizing map topologies applied to segment microstructures from metallographic images. However, the results obtained by self- organizing map neural network were not so good

Table 3: Different test methods.

Data size in ANN

The acceptance by industrial perspective has to be aligning with research perspective. Hence, selecting data size must reflect things have been practice by many researchers. The term data size is use instead of sample size because of in an ANN the deal data is not on sampling but the whole collected data. The uses of data size by previous researchers are not based on statistical technique that required certain amount of sample size for certain accuracy. This is due to the ANN is still able to function at limited data size. Based on Table 4, on average the data size is 211. Therefore for future parallel study this figure is the estimation data size.

ANN network setup

The data or digital images are set to be used for training, validation and apply network stage of processes. Special attention on the distribution of data so that instances of all defect type are included in each stage of process. Approximately 70% for training data will be selected from entire data. The remaining 30% data will be split into 10% and 20% for testing and validation stage that suggested by Gang and Warren Liao (2002). Nodes' activation function setup at the input, output, and hidden nodes layers can be Linear, Logsigmoid, or Tan-sigmoid.

Ref	[13]	[6]	[14]	[6]	[17]	[19]	[21]
Size	147	381	24	375	180	220	150

Table 4: Pattern size.

Conclusion

ANNs as non-parametric classifier capable to detect weld defects, while it might be a supporting tool rather than a major one. Study that uses camera to capture the defects can be a way of switch human for the inspection. This can be done by an "offshoot of visual inspection, involve an inspection of an object without the inspector present in the test area" (Nikhil Jain, 2012, p.7). The captured image then undergoes operations that further analyse to detect the defects. A new study perspective can be opted in area of tests that never been conducted. Test such as LP, MPI and AE are among the tests that potentially to be explored. Besides, wide spectrum of tests under the ND tests can be picked either since not many researches done on these tests. Plus in other form of standpoint uncountable forms of frequency domain features are applicable so this should be look forward for studies. Other network in ANN are still many to be studied, classification operation can be done by Bidirectional.

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