Artificial Neural Network Based Prediction Techniques for Torch Current Deviation to Produce Defect-Free Welds in GTAW Using IR Thermography

N.M. Nandhitha

Abstract In recent years, on-line weld monitoring is the potential area of research. In this work, torch current deviation prediction systems are developed with Artificial Neural Networks to produce welds free from Lack of Penetration. Lack of penetration is deliberately introduced by varying the torch **current**. Thermographs are acquired during welding and hotspots are extracted using Euclidean Distance based segmentation and are quantitatively characterized using the second order central moments. Exemplars are then created with central moments as input parameters and deviation in torch current as the output parameter. Radial Basis Networks (RBN) and Generalized Regressive Neural Networks (GRNN) are then trained and tested to assess the suitability for torch current prediction. GRNN outperforms RBN in predicting the torch current deviation with 98.95 % accuracy.

Keywords GTAW · Lack of penetration · RBN · GRNN · Torch current deviation

1 Introduction

Welding is defined as the process of joining metals in industries. With the advent of automated welding, large number of weld pieces is produced within a short span of time. In spite of accurate parameter settings, defects do occur in welds. Hence these welds are sent to strict quality assessment before dispatched to the end users. Welds that do not satisfy the standards specified by American Society of Mechanical Engineers (ASME) are rejected. Rejection of weld pieces result in loss of time, money and manpower. Hence online weld monitoring is a potential area of research in recent years.

N.M. Nandhitha (✉)
Deparment of Electronics and Communications Engineering,
Sathyabama University, Chennai 600 119, India
e-mail: nandhi_n_m@yahoo.co.in

A. Nagar et al. (eds.), *Proceedings of 3rd International Conference on Advanced Computing, Networking and Informatics*, Smart Innovation, Systems and Technologies 43, DOI 10.1007/978-81-322-2538-6_14

On-line weld monitoring involves the following: Selection of a suitable Non Destructive Testing Technique (NDT) that uses sensors for capturing the defects in welds during welding, image segmentation techniques that accurately isolate the weld defects, appropriate features that exactly represent the defects and suitable non-linear systems for predicting the deviations in weld parameters. In this work, InfraRed Thermography is used as a NDT technique for on-line weld monitoring. It uses an IR camera that captures the heat patterns and maps it into thermographs. This choice is justified because of the following reasons: In Gas Tungsten Arc Welding (GTAW), the arc is formed between the metal electrode (Tungsten) and the weld plate. Heat produced by the arc melts the plate and forms a pool which in turn forms the weld. In nutshell, heat produced at the weld pool mostly determines the quality of the weld. Heat transferred into the weld pool is in turn dependent on the torch current, torch speed etc. Hence heat can be used to assess the weld quality.

This paper is organized as follows: Related work is described Sect. 2. Section 3 provides the proposed methodology. Results are discussed in Sect. 4. Conclusions and future directions are provided in Sect. 5.

2 Related Work

Considerable research is carried out in the area of weld pool monitoring using thermal cameras. Also suitable signal and image processing techniques for analyzing thermal signatures obtained from both active and passive thermography are also cited in the literature. Sreedhar et al. [1] inferred that thermal analysis of weld pool has distinct features for defective and defect free welds. Vasudevan et al. [2] developed a computer controlled GTA machine by using Infrared thermography for sensing the characteristics of the weld pool. Leksir et al. [3] proposed an on-line weld quality monitoring system for Submerged Arc Welding (SAM). In the proposed technique, weld plates are in motion whereas the welding equipment is stationary. Weld pool temperature is used as an indicator for weld quality assessment. Fuzzy logic is then used to assess the weld quality as poor or fair or good. Swiderski and Hlosta [4] used pulsed eddy current stimulated thermography for the assessment of joints' quality in metal sheets. It was concluded that thermal contrast is better than vibrothermography. Aitor Garcia De La Yedra et al. [5] inferred that Discrete Fourier Transform (DFT), Discrete Wavelet Transform (DWT) and Thermographic Signal Reconstruction (TSR) results in enhanced weld quality assessment from thermal images. In all these literatures, it is found that the research has not proceeded to predicting the deviations in the physical parameters responsible for the defect. Hence in this paper, torch current deviation prediction system is developed using Radial bases. In order to train the network, input features are obtained from the descriptors used for representing the hotspots in weld thermographs.

3 Proposed Methodology

Of the various defects that occur in GTAW, Lack of Penetration is a very serious defect and results in immediate rejection of the weld pieces [6]. According to American Society of Mechanical Engineers (ASME), Lack of penetration is not permitted except when are of shallow and very short lengths [7]. Hence in this work, on-line weld monitoring system for Lack of Penetration is proposed using industrial Infrared Thermography is proposed.

3.1 Image Acquisition and Preprocessing

Lack of Penetration is deliberately introduced during by reducing the torch current from its optimal value. All the other physical parameters are kept constant throughout the experiment. Thermal videos are obtained using IR camera (during welding) and are stored as ".avi" files. As the acquired thermographs are videos, initially frames are extracted from these files. Also as the first 100 thermographs do not depict welding, they are not considered for segmentation and further processing. From the manual interpretation of the thermographs, it is concluded that the size and shape of the hotspot varies with that of the torch current. Figure 1 shows the hotspot variation for thermographs acquired with torch current of 70, 80 and 90 A (90 A is the optimal current). In the pseudocolouring of thermographs, hotspot is represented with yellow color. From the manual interpretation, it is found that as the torch current increases to the optimal value, the size of the hotspot also increases.

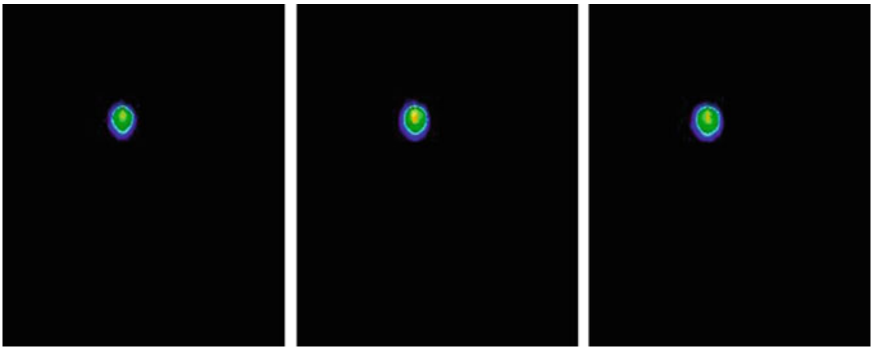

Fig. 1 Thermographs (frame 162) depicting the weld pool acquired with torch current of 70, 80 and 90 A

3.2 Image Segmentation for Feature Extraction

Of the various image segmentation techniques, Euclidean distance based image segmentation is used for extracting the hotspot. It is chosen as it does not involve the overhead of converting a pseudocolor thermograph into gray scale thermograph. Also the quantization error involved in color to gray scale conversion can be avoided. Euclidean Distance based segmentation accurately isolates the defect region (i.e. to the true size of the abnormality) and completely removes the undesirable regions from the weld thermographs. In Euclidean distance based segmentation, the Euclidean distance is calculated between the average intensities (Red, Green, Blue domains) of the hotspot and all the pixels (corresponding domains) in the thermograph. An output image is then obtained by retaining the pixels with Euclidean distance less than the threshold. Intensities of the other pixels are made as zero [8, 9]. Once the hotspot region is isolated, the hotspot is represented in terms of central moments. Central moments are chosen because they are shift and translation invariant. Exemplars are generated with frame number and the central moments as input parameters and torch current deviation as the output parameter. The next task is to develop a non-linear predicting system that predicts the deviation in the physical parameter responsible for the defect. As the output parameter is also available for training the network, supervised neural networks are chosen.

3.3 ANN Based Classifiers

Initially Back Propagation Network was used for current deviation prediction. In this paper, feasibility of other supervised learning algorithms is studied. Two most commonly used networks that use radial functions are Radial Basis Networks (RBN) and Generalized Regressive Neural Networks (GRNN) [10]. Performance of these networks is dependent on the choice of the spread functions. Spread function should neither be large nor be less. Larger spread function results in fast but abrupt convergence while smaller spread function results in slow but accurate convergence. In this work, accuracy of prediction is the major concern. As the neural network predictors are pre-trained with the exemplar set and only the weight updated neural network is used for prediction, time complexity is not a major issue. The spread function for RBN and GRNN is 0.0001 and 0.7 respectively.

4 Results and Discussion

A set of 11439 exemplars were created of which two different sets of 5719 exemplars are used for training and testing. Performance of the network is shown in Table 1. From the Table 1, it is found that both RBN and GRNN results in accurate

Table 1 Performance evaluation of RBN and GRNN based predictors for torch current deviation

Desired deviation in torch current	Predicted deviation in torch current	
	From RBN	From GRNN
0.4	0.4	0.4
0.35	0.35	0.35
0.25	0.25	0.25
0.25	0.25	0.25
0.2	0.2	0.2

prediction for the shown set of exemplars. However there are deviations between few sets of actual and desired values in both the classifiers. It is reflected in the calculation of accuracy. It is found that GRNN has an overall accuracy of 98.95 % while RBN has only 86.71 %.

5 Conclusion

In this paper, feasibility of RBN and GRNN for the prediction of torch current deviation is studied for on-line weld monitoring. The performance is compared to that BPN based predictor. It is found that GRNN results in a better accuracy than both RBN and BPN for the test dataset that resembles the trained dataset. However the accuracy of RBN and GRNN for a different set if input parameters are only 13.64 and 25 % respectively. In order to improve the performance of the network, it is necessary to consider the shape and Fourier descriptors of the hotspot.

References

1. Sreedhar, U., Krishnamurthy, C.V., Balasubramaniam, K., Raghupathy V.D., Ravisankar S.: Automatic defect identification using thermal image analysis for online weld quality monitoring. J. Mater. Process. Tech. **212**(7), 1557–1566 (2012)
2. Vasudevan, M., Chandrasekhar, N., Maduraimuthu, V., Bhaduri, A.K., Raj, B.: Real-time monitoring of weld pool during GTAW using infra-red thermography and analysis of infra-red thermal images. Weld. World **55**(7–8), 83–89 (2012)
3. Leksir, Y.L.D., Bouhouche, S., Boucherit, M.S., Bast, J.: Submerged arc welding online quality evaluation using infrared thermography based fuzzy reasoning. In: 13th International Symposium on Nondestructive Characterization of Materials (2013)
4. Swiderski, W., Hlosta, P.: Pulsed eddy current thermography for defects detection in joints of metal sheets. In: 11th European Conference on Non-Destructive Testing (2014)
5. De La Yedra, A.G., Echeverria, A., Beizama, A., Fuente, R., Fernández, E.: Infrared thermography as an alternative to traditional weld inspection methods thanks to signal processing techniques. In: 11th European Conference on Non-Destructive Testing (2014)
6. Lancaster, J.: Handbook of Structural Welding, Processes, Materials and methods used in the Welding of Major Structures, pipelines and process plants, vol. 260. Abington Publishing, (1997)

7. Halmshaw, R.: Industrial Radiology, Theory and Practice, vol. 230. Chapman & Hall Publications, London (1995)
8. Gonzalez, R.C., Woods, R.E.: Digital Image Processing. Prentice Hall, New Delhi (2005)
9. Selvarasu, N., Nachiappan, A., Nandhitha, N.M.: Abnormality detection from medical thermographs in human using Euclidean distance based color image segmentation. In: Proceedings of 2010 International Conference on Signal Acquisition and Processing, pp. 73–75, (2010)
10. Freeman, J.A., Skapura, D.M.: Neural Networks Algorithms. Applications and Programming Techniques, Pearson Education (1997)