Defect Depth Estimation in Passive Thermography using Neural Network Paradigm

RUDI HERIANSYAH and S. A. R. ABU-BAKAR
Faculty of Electrical Engineering
Universiti Teknologi Malaysia
81310 UTM Skudai, Johor
MALAYSIA

Abstract: - Defect depth estimation from passive thermography data based on neural network paradigm is proposed. Three parameters have been found to be related with depth of the defect. Therefore, these parameters: the maximum temperature over the defective area (T_{max}), the temperature on the non-defective or sound area (T_{so}), and the average temperature (T_{avg}) of the inspected area have been used as input parameters to train multilayer perceptron neural networks. For verification of the proposed scheme, NN has been tested with trained and untrained data. The correct depth estimation is 100% for trained data and more than 98% for untrained data. The result shows a great potential of the proposed method for defect depth estimation by means of passive thermography.

Key-Words: - Depth estimation, Passive thermography, Numerical modeling, Neural network

1 Introduction

Infrared thermography (IRT) is a technique 'to see the unseen'. It uses the distribution of surface temperatures to assess the structure or behavior of what is under the surface [1].

IRT has gained its popularity in the last few decades since it is non-contact, large area of inspection, easy data interpretation, and free from dangerous radiation. One disadvantage maybe from this technology is that the expensive cost of a thermal detector compare to, for instance, another thermal reading device like a thermocouple. But as the advancement of optoelectronic technology and imaging instruments, the mass production of these equipments tend to make the cost of them come into a reasonable range.

IRT has been successfully applied to electrical, mechanical, petrochemical, building and structures, material testing, industry, medical, and many others various applications [3], from breast cancer detection [4] to SARS (severe acute respiratory syndrome) diagnosis [5], from aircraft inspection [11] to heritage buildings application.

There are two approaches when applying this kind of technology: (1) active and (2) passive thermography. In active thermography, an external or internal source of heating energy is needed to assess the internal integrity of inspected object. But in passive thermography, any heating source is not needed since the radiated energy of the inspected object is high enough since then the temperature gradient between defective and non-defective area is so obvious and can be read by a thermal camera.

One of active research by employing IRT technology is in detecting the defect and estimating the depth of that defect. Inspection of graphite-epoxy composites and CFRP (carbon fiber reinforced polymer) by means of active thermography is one of popular application. Maldague [1-2] shows some applications of these materials inspection. Defect detection is commonly has the purpose to assess the condition of the surface of the inspected object. Quantitative thermography uses this data for defect sizing. In defect depth estimation, the target is the subsurface defect and this is important to assess the internal condition of the materials. Both defect detection and depth estimation are usually combined to make a comprehensive analysis of the inspected object quantitatively.

For depth estimation, few researches have been conducted. Neural network technique is a common application for this purpose. Saintey and Almond [6], used finite difference modeling to generate input training data for neural network interpreter to determine defect size and depth. Darabi [7], did a similar approach in which he used three dimensional heat transfer models to generate synthetic data to train neural network depth estimator by means of active thermography. All existing depth estimation based on NN [6-11] make use active thermography. This paper uses simulated data generated by a finite element method as the input parameters to train NN for defect depth estimation in a passive thermography scheme.

2 Numerical Modeling

Numerical modeling is a precious tool in IRT, especially since it can provide limits to the effectiveness of the thermal nondestructive testing (TNDT) technique and also the possibility of considering different defect geometries and determining their detectability without the expense of making and testing the corresponding specimens [1-2]. Another advantage of this kind of study is to generate the synthetic data for other uses in IRT as have been used in defect depth estimation in the previous researches [6-11].

This paper employs a finite element modeling (FEM) to study the temperature behavior of a high temperature wall and to derive the parameters related with depth of the defect.

It has been found in the previous work [12] through heat transfer modeling using FEM that there is a strong interdependence between the defect depth and maximum temperature behavior in thermal images of a furnace wall.

The model [12] to study other related parameters as shown in Fig. 1. consists of a multiple layers wall of a furnace made of firebrick (L = 22 cm, k = 1.436 W/m.K, Cp = 0.96 J/kg.K, ρ = 2300 kg/m3), insulation wall (L = 11 cm, k = 0.225 W/m.K, Cp = 1.3 J/kg.K, ρ = 1200 kg/m3), ceramic fiber block (L = 6 cm, k = 0.116 W/m.K, Cp = 2.8 J/kg.K, ρ = 430 kg/m3), and AISI 316 stainless steel (L = 0.5 cm, k = 16.3 W/m.K, Cp = 499.99 J/kg.K, ρ = 8000 kg/m3). Where L = wall thickness, k = thermal conductivity, Cp = specific heat, and ρ = density. Firebrick is the hot-face wall and steel is the cold-face (outer surface) wall. Analysis concentrates only on area of 100 cm × 50 cm (Fig. 2).

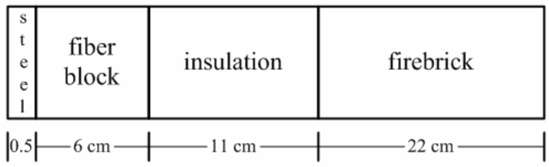

Fig.1 Typical four layers furnace wall

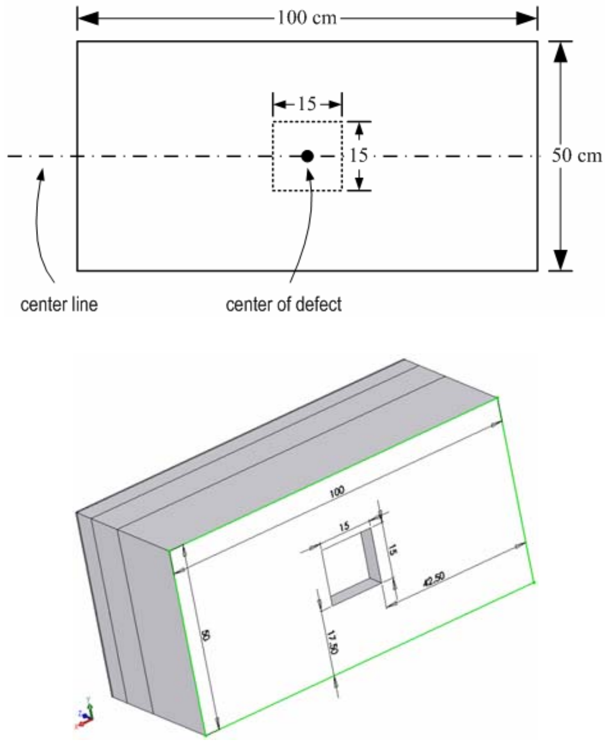

Fig.2 Area of analysis: front view (top), back view (bottom)

For passive thermography study, it is assumed that the temperature has been at its steady-state condition, in our case, the hot-face wall temperature assumed constant at 1000^{o}C, with ambient temperature to be at 25^{o}C. Adiabatic boundary conditions are applied to the four sides of the wall. Losses due to convective (h = 10 W/m2.K) and radiative (ε = 1) heat transfer occur from the outer surface (cold-face) wall. Spalling defect is simulated as a void with size of 15 cm^2 within hot-face wall (Fig. 2).

After simulating the model, the following results are obtained. Fig. 3 shows the relationship between defect depth and maximum temperature T_{max} (measured at the center) outer wall. It is clear that the deep defect reflects higher temperature distribution on steel wall over defective area.

As the temperature increases due to the defect depth, the average temperature T_{avg} for the outer wall will also increase as shown in Fig. 4. The same situation is also observed for the temperature on the sound (non-defective) area T_{so}. Fig. 5 shows temperature values on a user selected node and its variation with defect depth.

3 Depth Estimator

Artificial neural network is a simple abstraction of biological neurons. Networks of these artificial neurons do not have a fraction of the power of the human brain, but they can be trained to perform useful functions [13].

In this paper, a multilayer perceptron (MLP) was trained to have the capability in the estimation of defect depth which may occur within the furnace refractory.

As already shown in the previous section, the maximum temperature over the defect area (T_{max}), the temperature on the sound area (T_{so}), and the average temperature (T_{avg}) for the whole wall are indeed related to the defect depth. Therefore, these three parameters are employed in the NN training for depth estimation. These parameters are extracted from the numerical modeling as discussed in the previous section. For the training purpose, the following defect depths are used: 38.5, 37.5, 36.5, 35.5, 34.5, 33.5, 32.5, 31.5, 30.5, 29.5, 28.5, 27.5, 26.5, 25.5, 24.5 cm. It is worthy to note that defect depth in our case is measured from the outer face (steel) wall.

The artificial neural network shown in Fig. 6 was found to ‘train’ efficiently on the supplied data. The input data for ANN training are T_{max}, T_{so}, and T_{avg} and the corresponding values of defect depth were used as the outputs.

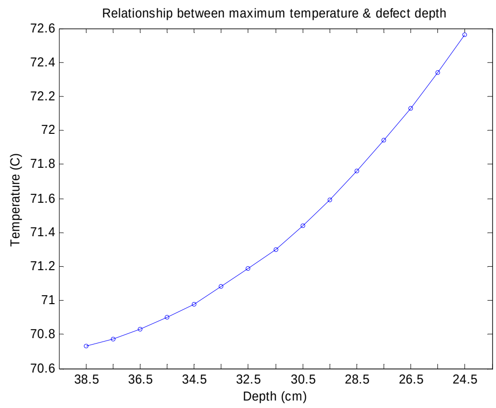

Fig.3 Relationship between maximum temperature T_{max} with defect depth

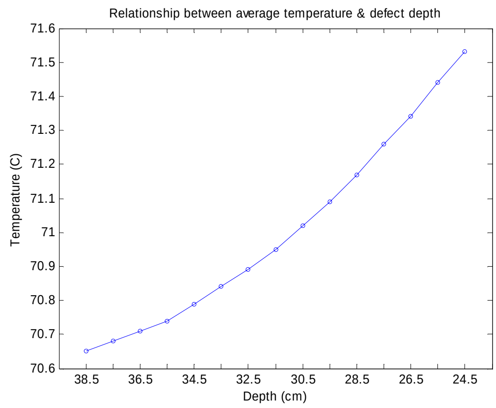

Fig.4 Relationship between average temperature T_{avg} with defect depth

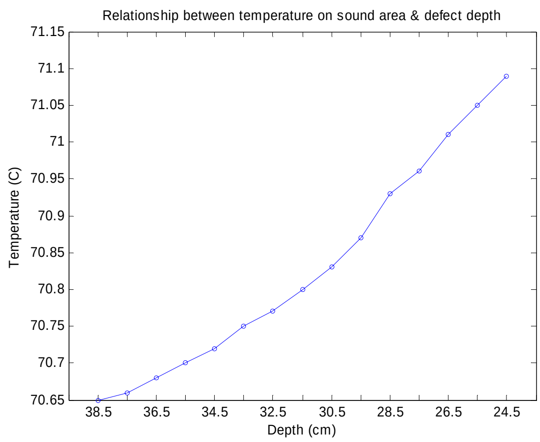

Fig.5 Relationship between temperature on sound area T_{so} with defect depth

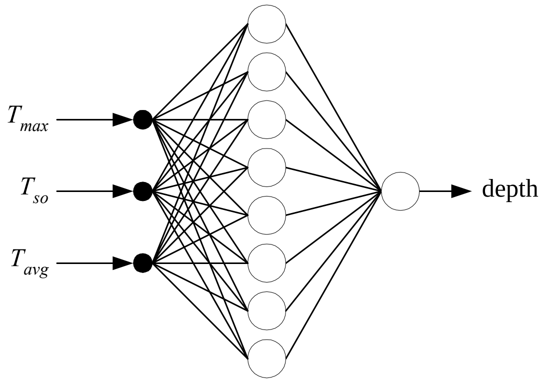

Fig.6 ANN architecture for depth estimation

Fig. 7 shows the defect depth estimation by neural network for the trained data as compared to the actual depth. It is clear that the entire trained depth can be estimated correctly by NN.

Fig. 8 shows the depth estimation for untrained data (of depth 39, 38, 37, 36, 35, 34, 33, 32, 31, 30, 29, 28, 27, 26, and 25 cm respectively from the outer surface wall). Error depth estimation for this untrained data is shown in Table 1. From the table, the depth estimation error is less than 1% except for 25cm depth (1.6% error). This result indicates that the NN has achieved its generalization condition even for the unknown data.

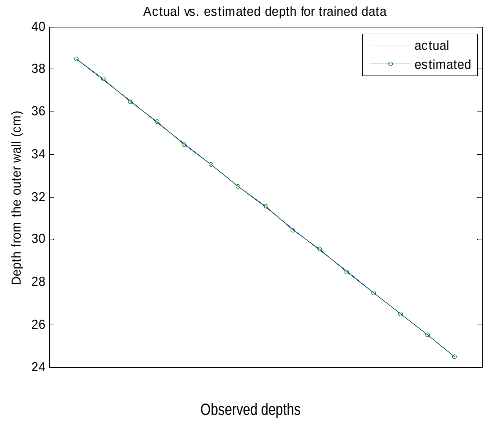

Fig.7 Estimated depth for trained data

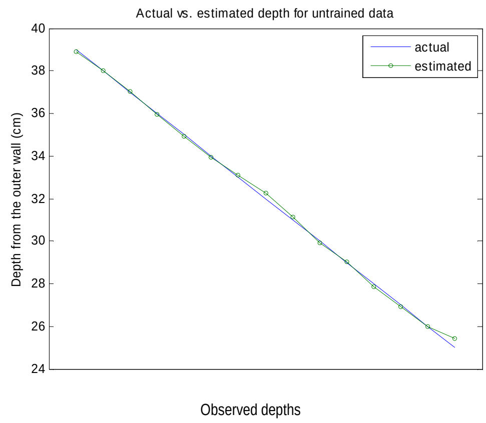

Fig.8 Estimated depth for untrained data

4 Conclusions

It has been shown from the result in the previous section that the depth estimation by using neural network paradigm both for trained and untrained data is quite satisfactory.

Neural network paradigm with its ability to learn and adapt to a new pattern has a great potential for the estimation of the defect depth. This paper has demonstrated on how to employ NN paradigm for depth estimation in a passive thermography scheme.

Table 1 Error for depth estimation with untrained data

Actual Depth	Estimated Depth	Error	
		Magnitude	Percentage
39	38.9	0.1	0.26
38	38.0	0.0	0.00
37	37.0	0.0	0.00
36	35.9	0.1	0.28
35	34.9	0.1	0.29
34	34.0	0.0	0.00
33	33.1	0.1	0.30
32	32.3	0.3	0.94
31	31.1	0.1	0.32
30	29.9	0.1	0.33
29	29.0	0.0	0.00
28	27.8	0.2	0.71
27	26.9	0.1	0.37
26	26.0	0.0	0.00
25	25.4	0.4	1.60

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