Automatic Defect Detection and Depth Visualization in Mild Steel Sample Using Quadratic Frequency Modulated Thermal Wave Imaging

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Abstract. Deeper defect detection and depth resolution capabilities of quadratic frequency-modulated optical stimulus became a viable approach for material inspection in active infrared non-destructive testing modality. But the limitations of complex and non-linear analytical models associated with processing techniques propel towards automated defect assessment techniques in infrared thermography. This paper introduces a deep neural network-based automatic defect detection and depth visualization technique in quadratic frequency modulated thermal wave imaging. The neural network classifier uses the modified loss function of a one-class support vector machine to classify defects. The regression network estimates the depth of classified defects. A mild steel specimen with artificial delaminations is numerically modeled and excited by a quadratic frequency-modulated heat flux. The proposed network classification and regression performances are qualitatively assessed using testing time, accuracy, and mean squared error as a figure of merits.

Keywords: Artificial neural network, Automatic defect detection, Numerical simulation, and Quadratic frequency modulated thermal wave imaging.

1. Introduction
Non-contact, non-invasive, safe, remote, and wide-area inspection capabilities prefer active thermography (AT) as suitable non-destructive testing (NDT) technique in the recent past. AT utilizes an optical heat flux to excite the test sample, which induces diffusive thermal waves that diffuse deep into the test object. These diffusive thermal waves reflect from subsurface layers if any inhomogeneity present underneath the surface and further heat up the test sample surface. An infrared camera captures this thermal map, further analyzed for the qualitative and quantitative extraction of subsurface anomalies [1].

Various excitation techniques emerged in AT, such as pulsed excitation in pulse thermography (PT), periodic stimulus in lock-in thermography (LT), and advanced coded excitation schemes of non-stationary excitation [2-5]. The advancements of non-stationary stimulation techniques overcome the limitations of elevated peak power stimulus in PT and repeated investigation in LT using low peak power stimulus modulated by a band of low frequencies [4, 5]. Among various non-stationary excitation
schemes, quadratic frequency modulated (QFM) optical heat flux is gaining interest due to its deeper
defect detection and depth resolution capabilities [5]. Various processing approaches, such as principal
component analysis, pulse compression, and chirp z transform, became famous processing approaches
in QFMTWI [7-10]. Pulse compression and chirp z transform provide depth resolution and
quantification facilities of subsurface anomalies with complex and non-linear analytical models [8-10].
To replace the complex, non-linear analytical models and human intervention, various automatic defect
detection, and visualization systems enabled with machine learning techniques are emerging in infrared
thermography [2].

In thermography, defect detection, classification, and quantitative depth estimation problems are
treated as binary classification, multi-class classification, and regression problems in machine learning.
Hence, various artificial neural networks (ANN) evolved in conventional infrared thermography for
composite material inspection [11]. Different feature vectors from the observed thermal response in PT
are extracted and fed to train neural networks for defect detection [2], classification [12], and depth
estimation [13], respectively. On the other hand, a back-propagation neural network optimized by
particle swarm optimizer is introduced in QFM stimulus to map their analytical model for defect
detection followed by depth estimation in composite samples [14]. Following that, a classification and
regression-based decision tree was implemented to detect and estimate the depths of defects in
composite materials [15, 16]. In the recent past, defect detection in QFMTWI is advanced with various
distance, density-based supervised classification techniques, and clustering-based unsupervised
classification techniques [17, 18].

The present article introduces an artificial neural network to classify defects and estimate their
depth using a mild steel sample’s thermal response. The proposed multi-layer deep neural network
trained using a few thermal profiles randomly selected from the temporal thermal map of mild-steel
specimen excited by QFM optical stimulus. The proposed network’s classification and regression
performance is tested by feeding the total thermal response and analyzed using performance metrics
such as testing time, classification accuracy, and mean squared error.

2. QFMTWI

In QFMTWI, a band of low frequencies is provided to modulate the moderate peak power heat flux
illuminating from a set of halogen lamps to excite the test object [10]. The experimental schematic of
QFMTWI is given in the fig.1. The heat flux induces thermal waves that propagate into the test object,
contributing a thermal contrast on the surface due to reflections from sub-surface anomalies. A 1-
Dimensional heat diffusion equation used to analyze the thermal wave propagation as given by [1]

$$\frac{\partial^2 T}{\partial Z^2} = \frac{1}{\alpha} \frac{\partial T}{\partial t}$$  \hspace{1cm} (1)

Fig 1. Schematic diagram of the QFMTWI setup.
$T(z, t)$ is the object's temperature over the defect situated from a distance $z$ from the surface, and $\alpha$ is the test sample's thermal diffusivity. The mathematical representation of the QFM stimulus is given by [5]:

$$Q(t) = Q_0 e^{(a t + b t^2)}$$  \hspace{1cm} (2)

Where $b$ is the frequency range, $a$ is the opening frequency, and $Q_0$ is the lamp's peak stimulation power. From these boundary conditions of the test object, the diffusion equation in Eqn. 1 is solved for a point on the heating side of the test object result in temperature is given by

$$\tilde{T}(x,s)=Q(s)\frac{e^{-\sigma x}}{k\sigma}$$  \hspace{1cm} (3)

Where $\sigma$ is the thermal diffusion length $\tilde{s}$ is the Laplace transform of the chirp.

3. Artificial Neural Networks (ANN)

Artificial neural networks (ANN) are inspired by the human brain's working principle such that they have input receptors and output decision layers with intermediate hidden layers consisting of multiple nodes interconnected with each other. This architecture helps ANN's to develop a non-linear relationship to efficiently generalize the given data to their respective classes or labels. Similarly, defect detection, classification, and depth estimation has been achieved by ANN's in infrared thermography [2, 3, 6-9].

Hence, the present work introduces a deep back propagation neural network with four hidden layers and an output layer to generalize given thermal response to classify defects and estimate their depths. Table.1 presents the proposed ANN network architecture. The hidden layers are activated by the Rectified Linear Unit (ReLU) activation function. A dropout layer with a dropout rate of 0.5 is added before the final decision layer avoids over-fitting the network. The final output layer consists of one neuron that gives +1 or -1 or depth of the defect values in classification and regression tasks. The last layer is activated by the sigmoid and linear activation functions in the classification and regression networks. During the defect classification, the loss function used is hinge loss widely used for maximum-margin classifiers [19] as given in Eqn. 5, and the mean squared error loss is used for regression analysis [13] is shown in Eqn. 6 respectively.

Hinge loss: \( L(y) = \max(0, 1 - t \cdot \hat{y}) \) \hspace{1cm} (5)

Mean Squared Error: \( L = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \) \hspace{1cm} (6)

\( Y \) is the prediction, \( t \) is the intended output or actual class of the given data in hinge loss. On the other hand, \( y \) is the real value and \( \hat{y} \) is the estimated value, and \( n \) is the batch size in mean squared error loss.

Table.1 Neural Network Architecture.

| Layer   | No. of Neurons | Activation |
|---------|----------------|------------|
| Input   | 625            | ReLU       |
| Dense   | 350            | ReLU       |
| Dense   | 175            | ReLU       |
| Dense   | 120            | ReLU       |
| Dense   | 75             | ReLU       |
4. Numerical Simulation

A numerical simulation is carried out to model the thermal response of mild steel samples with delamination defects of different sizes at varying depths excited by a quadratic frequency-modulated heat flux. The heat flux modulated with a band of low frequencies from 0.01Hz to 0.1Hz is imposed on the test object for 100 seconds, and the corresponding thermal response is recorded at 25 samples per second [10]. A fine tetrahedral mesh is selected for numerical simulation.

The recorded thermal response is linear fitted and centered on its mean to extract a dynamic component. Fig. 2 represents the simulated sample layout and dynamic thermal profile extraction in a, b, respectively. Each thermal response is associated with its respective ground-truth value for classification and regression tasks. For the classification task, thermal profiles at the sound region are labeled as +1, and the thermal profiles at defective areas are marked as -1. On the other hand, thermal profiles at defective and sound areas are given with respective depth of the defect and sample thickness values for regression analysis.

5. Results and Discussion

From the acquired thermal response, the training data set is formed by randomly selecting 1150 (800 from the non-defective region and 350 from the defective area) thermal profiles. During the training process, network over-fitting is monitored, and training performance is validated by using 20% of training data as a validation set. The training and validation loss curves of the network during training with Adam optimizer are given in fig. 3, from which it is observed that the model is training correctly.
Fig. 3. Training performance of proposed ANN.

The current implementation is processed on an Intel i3 CPU with 2.4GHz clock speed supported with 8GB internal memory and 2TB HDD in python 3.6 environments. During classification, the network is trained for 500 back-propagation iterations for 70 seconds with a loss function given in Eqn. 5, and Tanh activation is used in the final output layer to predict whether the given thermal response belongs to -1 or +1 class. While testing, the entire thermal response of the test sample is fed to the network, and the classified result is shown in fig. 4. a, whereas 4.b presents the comparison between real and predicted labels. The testing took 1.24seconds and resulted in 90% accuracy in defect detection.

Fig. 4. a. Defect classification in mild steel sample using ANN classifier, b. Comparison between True label to predicted label.

On the other hand, defect depth estimation plays a significant role in quantitative infrared thermography. Hence, the network is trained with mean squared error loss function, given in Eqn. 6, for 750 back-propagation iterations with linear activation function at the final decision layer for 125seconds. While testing, the entire sample thermal response is fed to the network. The corresponding estimated depth of each test profile is presented in fig. 5.a and 5.b give a comparison between actual depth and predicted depth. The mean squared error observed between predicted and actual depth is 0.27mm.
Fig. 5. a. Defect depth estimation in mild steel sample using regression network and b. Comparison of real and predicted labels.

6. Conclusion
The present article introduces a deep back propagation neural network to classify defects and quantify their depths in QFMTWI modality. A numerical simulation is carried out to model the thermal response from a mild steel sample having flat-bottom holes at different depths with different sizes. It is concluded from the observations that the proposed network efficiently detects the subsurface anomalies and estimates their depth with less deviation from actual values. The future works extended to analyze more deep learning algorithms to improve the classification and depth estimation accuracies in QFMTWI for various test samples.

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