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Deep Autoencoder for Automatic Defect Detection in Thermal Wave Imaging

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Abstract

Automatic defect detection enabled with machine learning based processing techniques is the recent trend in thermal wave imaging based non-destructive testing. In this context, automatic defect detection can be regarded as a classification problem, distinguishing defective and non-defective regions using the respective thermal profiles of a test sample. This article introduces and analyses a deep neural network autoencoder for automatic defect detection in quadratic frequency modulated thermal wave imaging. The proposed methodology is validated experimentally on the thermal response of carbon fiber reinforced polymer specimen with flat-bottom holes at different depths. Machine learning assessment metrics suggest that the proposed autoencoder provides automatic defect detection in composite samples.

Keywords: Automatic defect detection, Autoencoder, Carbon fiber reinforced polymer, Quadratic frequency modulated thermal wave imaging,Thermal Wave

1 Introduction

Inspecting the industrial objects and assessing their integrity without their future usefulness paved the way for various non-destructive testing techniques (NDT). Among various NDT techniques, thermal wave diffusion-based active infrared thermography is gaining interest due to its non-contact, whole field, Subsurface analysis capabilities in cost-effective

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manner. Active thermography (AT) observes the temperature map over the test surface using an infrared camera under a controlled stimulus. Further, the observed thermal response is processed, and a corresponding contrast parameter is used to distinguish the defects. Based on the excitation, AT is further divided into two classes as conventional and non-stationary thermography [1]. A short duration high peak power stimulus from flash lamps in pulsed thermography (PT) and a periodic excitation with moderate peak power from halogen lamps in lock-in thermography (LIT) are conventional and widely used thermographic approaches [2, 3]. However, the non-uniform illumination of high peak power heat sources, non-uniform radiation from the test sample, environment noise and receiver sensitivity affects the inspected thermal response. On the other hand, moderate peak power optical heat flux overcomes these limitations, but the proportionate relation between frequency and diffusion length recommends repetitive experimentation to assess the entire depth axis of the test sample with different low frequencies.

Surpassing these limitations in conventional thermography, non-stationary excitation schemes with various phase or frequency coded stimulus have been introduced in the past two decades [4-6]. Non-stationary stimulations illuminate low energy optical source over the test object modulated by a band of low frequencies or variable bit rates to map the average energy projected by a pulsed stimulus [7]. The modulation of excitation source with low frequencies contributes to the diffusion of thermal waves generated over the sample surface to different depths, leading to the detection of defects at different depths in single experimentation. In the recent past, quadratic frequency modulated optical stimulus is gaining interest due to its deeper depth probing and enhanced depth resolution characteristics [5]. Though the excitation schemes are advanced, a suitable processing technique is required to extract the salient features of the respective processing technique. Processed thermal response results in massive thermographic data from which extracting the defect signature for detection and quantification requires an experienced observer and complex and non-linear theoretical models. In the recent past, machine learning based processing techniques have been introduced in AT as an automatic approach to replace the human intervention and complex theoretical models [8-18].

2 Literature Review

In thermography enabled with machine learning, defect detection is considered as a classification task and depth estimation as a regression problem. Artificial neural networks (ANN) and support vector machines have been introduced in conventional thermography to classify and quantify the defects in composite samples using conventional thermography approaches in the late 1990's [2, 8]. However, the trend in automatic defect detection is enabled in the past decade with various deep learning architectures to meet the NDT's current or 4th revolution. Yousefi in [9] introduced a pre-trained deep learning model to distinguish the defects in thermograms in conventional thermography and given their score using spectral angle mapping, which lead the way for deep learning architectures. In [10], Saeed applied three object localization techniques to locate the defects in the thermogram sequence and further used their pre-trained ANN model to estimate the depths of the defects. On the other hand, Luo in [11] treated defect detection as a classification and schematic segmentation task and introduced a 3-stage long short term memory (LSTM) model and u-Net based image segmentation architecture for defect detection in composite samples in PT. In contrast, Dudzik in [12] introduced decision tree based classification and depth quantification models in PT. The recent past witnessed the introduction of LSTM based models for defect depth estimation in composite structures using PT [13, 14]. However, the thermographic data is scarce, and an augmentation technique through generative adversarial networks is recently proposed by Kiaxin Liu [15]. On the other hand, a thermographic dataset of composite samples with delamination defects inspected in transparent and reflection modes using PT is made available by Jorge in [16].

The advancements in deep learning for defect detection in LIT is proposed by Yanpeng in [3] using a two-stream similarity prediction network using one-dimensional convolutional neural network layers. In contrast to conventional thermography enabled with machine learning, Vijayalakshmi in [17, 18] introduced ANN and Decision tree based approaches for automatic defect detection in composite structures in quadratic frequency modulated thermal wave imaging (QFMTWI). However, deep autoencoder based architectures are discussed in ultrasonic NDT to enhance the defect signature by regenerating the acoustic signals in [19], which is further extended to infrared thermography to regenerate thermograms for enhanced defect detection [20].

3 Proposed Methodology

The present article treats the defect detection in infrared thermography as an anomaly detection problem since the industrial composites present high strength and are prone to less probability for defect generation. The thermal profiles at the sound region present similar characteristics (Attenuation and time delay) whereas the thermal profiles at the defective region possess different characteristics based on the size and depth of the defect [17]. On the other hand, detecting a small defect at subsurface layers is covered by a small number of temporal thermal profiles, making them anomalous data or outliers. Anomaly or outlier detection is a challenging task in machine learning achieved by various algorithms, including autoencoders (AE) [21].

Autoencoder is a generative model that generates or copies the input data with significantly less error, which made it to be used in various applications [22].

The structural details and operation of autoencoder is presented in the next section. Here, automatic defect detection is achieved through training the AE on a few sound regions thermal profiles and a threshold on training data error is fixed, which is used to distinguish thermal profile at the defective region in the testing phase. The proposed methodology is presented in a flowchart as given in fig. 1.

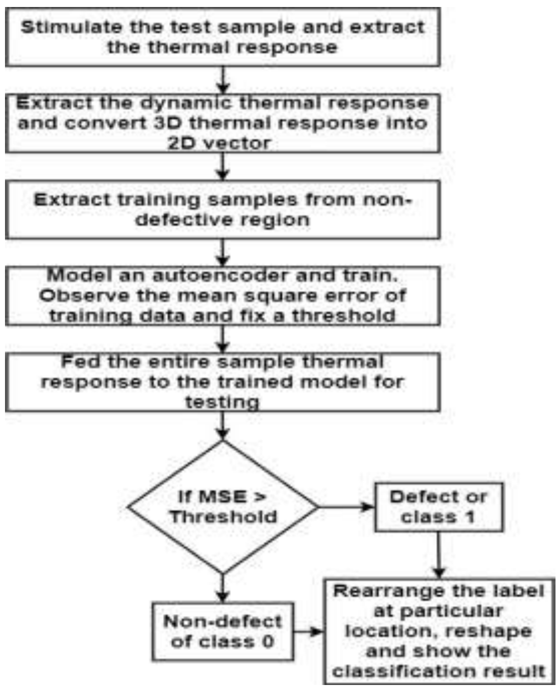

Figure 1 Flowchart of the Proposed Methodology.

4 Mathematical Modelling

In AT, the front side of the object under test is excited by a controlled optical stimulus through a set of optical sources. The imposed optical stimulus generates thermal waves over the surface of the specimen, which further propagates into the test sample through diffusion phenomenon, any subsurface anomaly or material inhomogeneity reflects these thermal waves and further heats up the surface and creates thermal contrast which is observed through an infrared imager. The diffusive thermal waves can be expressed mathematically by a one-dimensional heat diffusion equation as given by [1]

$$\frac{\partial T}{\partial t} = \frac{1}{\propto}\frac{\partial^2 T}{\partial x^2} \tag{1}$$

Where α is the thermal diffusivity of the test sample. In the present case, the optical stimulus of intensity Qo is modulated by a band of low frequencies with a bandwidth b with initial frequency a for the time period of t as given by [5]

$$S_{QFM}(t) = Q_0 e^{-j(a+bt^2)t} \tag{2}$$

The experimental schematic of QFMTWI is presented in fig. 2. Solving Eqn. 1 through Eqn. 2 and sufficient boundary conditions results in a temperature over the object surface T(x,t).

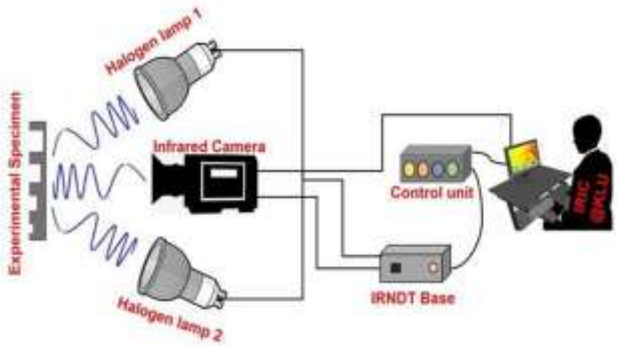

Figure 2 Experimental schematic of QFMTWI.

The observed temporal thermal response at a pixel location is contributed to the defective or non-defective region of the test sample. In the present case, a deep neural network based autoencoder is employed for automatic defect detection in the test sample. Autoencoder is a generative model that learns unsupervised to copy or generate input data. AE is a combination of two symmetrical deep neural networks sharing a standard hidden layer at the end that is known as a coded layer or latent space, as shown in fig. 3. The two deep neural networks are encoder and decoder, where the input thermal response is given to the input end, which is compressed by the hidden layers of the encoder network. In some cases, the compression is generalized to principal component analysis at the latent space in the encoder network with linear activation functions.

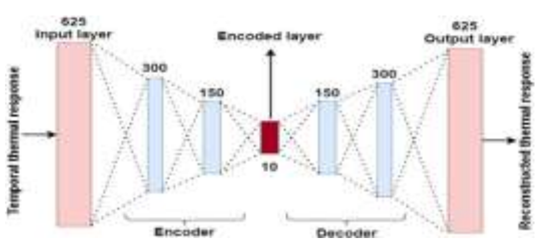

Figure 3 Deep Neural Network Autoencoder.

Similarly, the compressed features in the latent space present the encoded representation of the thermal response. This is further decoded into the original thermal response through the back propagation of weights. The theoretical representation of an AE is given by [22]

$$\arg\min_{e,d} E\left[\Delta\left(x, d \circ e(x)\right)\right] \tag{3}$$

Where, e is the encoder, d is the decoder, x is the input, Δ is the reconstruction loss, and E is the expectation of x. During training, few thermal profiles from the non-defective region are selected, and the respective error of the proposed AE model is observed, and a threshold value on the error is fixed. In the testing phase, entire sample thermal response is fed to the trained model results in a regenerated thermal response that can be used as an augmented dataset for further training of other deep learning architectures. In addition, the error on testing data is compared with the threshold, and thermal profiles at defective and non-defective thermal profiles are classified [23].

5 Results and Discussion

To validate the proposed methodology, experimentation is carried out over a carbon fiber reinforced polymer (CFRP) sample with flat bottom holes of different sizes at different depths as shown in fig. 4. a. The front side of the test sample is excited with a 2kw optical stimulus from a set of halogen lamps, which is modulated by a band of low frequencies of 0.01-0.1Hz for 100 seconds. A FLIR A655SC thermal camera observes the respective thermal response at 25 frames per second. The thermal camera operates in a spectral range of 7.5 to 14µm and having sensitivity to a small change in the temperature of 30mk. From the observed thermogram sequence, a region of interest of the test sample covers the test sample in 366x366 pixels in 2500 frames. During excitation, the wave-like stimulus of QFM excitation requires negative heating, which is altered by adding a DC offset that leads to a temperature rise in the recovered thermal response. This temperature rise in the thermal response does not provide any quantitative information and is further removed by a proper fitting technique that results in a dynamic component of the thermal response. Fig. 4.b represents the extraction of dynamic thermal response from the observed raw thermal response.

Further, each temporal thermal profile in view is down sampled by decimation of 4 that results in the thermal response with a length of 625 samples to reduce the computational complexity. The down sampled 3D thermal response is reshaped into a 2D vector by arranging the temperature over each pixel in rows and their respective temporal variations along with the columns. Further, each thermal response is associated with respective labels of 0 and 1 as the thermal profile at non-defective region is associated with 0 and the defective region is associated with 1.

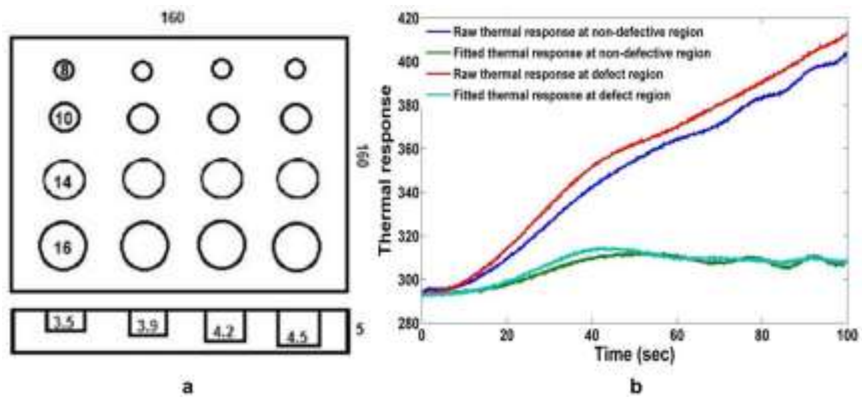

Figure 4 a Layout of CFRP test sample and **b** extraction of dynamic temporal thermal profile.

Further, a training data set of 1000 thermal profiles is extracted randomly from the non-defective class to form a normal class dataset. The training and the testing thermal responses are normalized before feeding to the network.

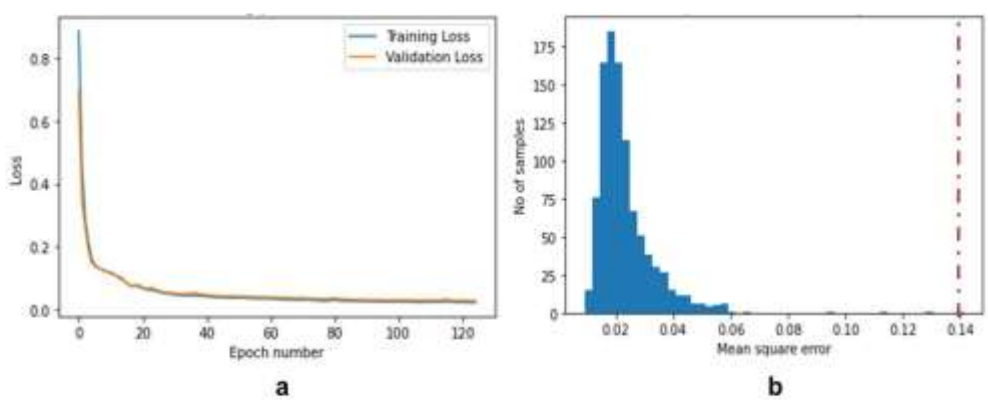

Figure 5 a Training performance of Autoencoder and **b** Histogram of mean square error on training data and threshold in red dotted line.

The proposed deep autoencoder is trained on the training data for 125 back propagation iterations for 25 seconds with Adam as an optimizer and mean squared error as the loss function. The present work is implemented in an Intel i3 CPU with 2GHz clock speed supported by 8GB memory and 2TB HDD in python 3.6.10 environment. During training, the network performance is simultaneously validated by splitting the training data into training and validation splits of 85% and 15%, respectively. The training and validation loss curves in fig. 5. a represents the proper training of the network without over-fitting. Further, the histogram of the mean squared error (MSE) on training data is observed and is shown in fig. 5. b. It is observed from the figure that the AE generates low error on the training data upon which a threshold is fixed at the maximum value in the histogram.

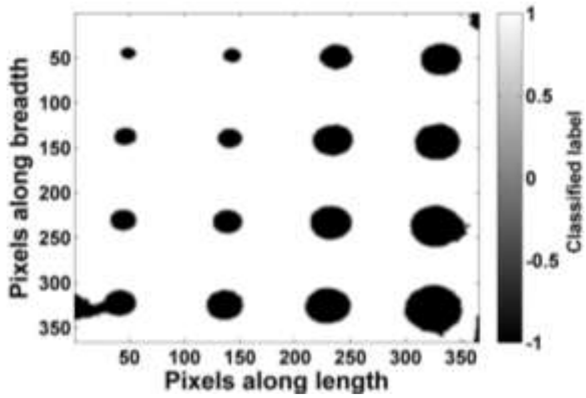

Figure 6 Classified Defects in CFRP sample using Proposed Deep Autoencoder.

Further, the entire sample thermal response is fed for testing, and the mean squared error on testing the thermal response is compared with the threshold and automatically annotated the respective profile label as 0 or 1. If the MSE is greater than the threshold, the thermal profile is associated with label 1, stating it belongs to the defective region and otherwise belongs to the sound region. Further, the resultant classification is reshaped to 2D and visualized as an image as shown in fig. 6, presenting the defect signatures as respective labels. Further, the classified labels are subjected to parametric analysis [23], which presents 95.35% testing accuracy with a precision rate of 0.88, recall of 0.74 and f1-score of 0.80 for defective thermal profiles. The observed classification report suggests that an efficient thresholding scheme must be implemented to achieve more accurate and precise defect detection in the composite sample.

6 Conclusion

The present article introduces a deep autoencoder based automatic defect detection methodology for composite inspection in QFMTWI. Defect detection is treated as an anomaly detection problem in machine learning, and the proposed autoencoder based approach present a prominent defect detection in the composite materials. It is also concluded that the autoencoder can be used as data augmentation technique and future deep learning algorithms can be trained from this augmented data. The present work will be extended to implement more deep learning architectures in QFMTWI for automatic defect detection and composite structures assessment.

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