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A STATISTICAL APPROACH FOR SUBSURFACE ANALYSIS IN NON-STATIONARY THERMAL WAVE IMAGING

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ABSTRACT

Infrared non-destructive testing makes use of captured surface temperature map over object surface to characterize subsurface features. This qualitative and quantitative analysis of subsurface anomalies widened the scope applicability due to its whole field, noncontact, non-invasive testing modality in addition to its suitability for testing of various materials. Augmented by the availability of various processing and testing methodologies it is gaining interest for surface and subsurface analysis. This paper introduces a qualitative methodology for subsurface analysis based on a classification using logistic regression and defect depth quantification using a linear regressive model developed for quadratic frequency modulated thermal wave imaging. The proposed methodology has been tested through experimentation carried over a carbon fiber reinforced plastic specimen with embedded flat bottom holes.

Keywords: thermography, carbon fiber reinforced plastics, regression.

INTRODUCTION

The infrared non-destructive testing (IRNDT) facilitates detection of surface and subsurface anomalies without causing any damage to the future usefulness of the object under investigation [1]. Being suitable for testing various materials, it is gaining popularity as a reliable evaluation tool for qualitative subsurface assessment. It makes use of captured temperature evolution over the test object to extract subsurface details by employing various activation and processing methodologies. It is classified into two approaches called as passive and active [2].

In active approach, test body is subject to a modulated stimulation, which produces a similar thermal perturbation in a thin layer over the surface of the test object. This perturbation contributes toa diffusive thermal wave inside the test object and further propagates. As obstructed by anomaly due to the alteration in diffusive rate originated by existing thermal in homogeneity, these propagating thermal waves produce a temperature contrast over the object surface at anomaly location [5]. Then the resultant transient temperature field is captured occurred on the investigated surface is recorded using an infrared camera.

This defect characterization is an inverse heat transfer problem intended for the determination of the defect depth and various other parameters [3]. Numerical modeling is used to get the basic method of the analytical form of relationships describing the defect depth estimation [3-4]. The most used methods for this purpose are the finite difference method or the finite elements method. In addition, to numerical models for the characterization and detection of defects, the algorithms based on statistical analysis of thermograms and regression models can be used [3]. The primary stage of detection is recording of a temporal sequence of thermograms called as data acquisition which gives a feature vector used for training. It consists of the input values obtained on the basis of the temperature rise occurring on the investigated surface.

Being suitable in maintaining the variance of the input data in the fitted coefficients, this paper employs a statistical method based on regression to detect the subsurface anomalies in a carbon fiber reinforced plastic specimen using non stationary thermal wave imaging.

METHODS AND MATERIALS

A. Classification stage

A fundamental concept related to a classification is the pattern being recognized. The classified pattern is defined as a p-dimensional observation. It is assumed that the pattern is fully described with p variables called features. Hence, the recognized pattern can be considered as a point in the p-dimensional space of features. In the case of the defect detection using the active thermography methods, the classified pattern can be a temporal evolution of temperature rise, recorded for the specified point on the surface of the investigated material sample [6] (i.e. recorded for the specified thermograms pixel). A classification stage employs a logistic regression which assigns the consecutive pixels in the thermograms of the investigated surface to one of the two classes representing a non-defect or defect area respectively. As a result, each pixel in the field of view on the surface of investigated sample is assigned a binary value depending on its status either 1 or 0. This stage primarily involves two modes namely training mode and testing mode. In training mode, a supervised approach of curve fitting is employed. Once the model was trained it was followed by a testing mode. In the predictionmode, thep-dimensional observation was given as input and the output was recorded as an output of the classification stage.

In the output, the logistic regression has two values representing non-defect and defect class respectively. The gradient descent algorithm sets the weights by minimization of the cost function. It enables to assign all the pixels to the non-defected areas or defected areas [7]. Then, the prediction can be performed. In general, the elements of the input data vectors are the representation of the temporal evolution of temperature, recorded for the pixel of the investigated surface. As a result, every pixel in thermograms is classified as a pixel belonged to the defected or non-defected area of the investigated sample.

B. Regression stage

Regression curve can describe a functional dependence between random variables representing measurements of physical quantities. The linear regression model can be used to estimate the defect depth using the thermograms of the sample. In this process, linear regression curve approximates the solution of the inverse heat transfer problem.

It consists of the N temperature values assigned to the particular pixel for every time instant. The size of the input vector is determined by the number of the time instants. The number of the training vectors is equal to the number of pixels in the considered field of view of the investigated material.

Linear regression model works in two modes: the training mode and the prediction mode. In the training mode, the samples created for every pixel in the field of view is applied to the inputs of the regression model.

Logistic regression

Logistic regressive model, as the primary concept of regression, is to map the random variables (features of trained inputs) on to the dependent variable (defect class) which is developed using the hypothesis.

$$h_\theta(x)=\theta_T x = \theta_0 + \theta_1 x_1 + \cdots \theta_n x_n \qquad (1)$$

Here θ_j are the parameters of the linear model.
x_j^i-the value of the j^{th} feature of i^{th} training sample, g is the sigmoid function.

$$g(z) = \frac{1}{1+e^{-z}} \begin{cases} (0.5,1] & z > 0 \\ 0.5 & z = 0 \\ [0,0.5) & z < 0 \end{cases} \qquad (2)$$

The cost function for this logistic model is given by the equation.

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m}[-y^{(i)}\log\left(h_\theta(x^{(i)})\right) - (1-y^{(i)})\log(1-h_\theta(x^{(i)}))] \qquad (3)$$

$y^{(i)}$ - Targets of the i^{th} training sample
m - Number of training samples

Linear regression

Linear regressive model, as the primary concept of regression, is to map the random variables (features of trained inputs) on to the dependent variable (depths) which is developed using the hypothesis.

Linear Regression model is based on the hypothesis $h_\theta(x)$

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \cdots \theta_n x_n \qquad (4)$$

Here θ_j are the parameters of the linear model.
x_j^i - The value of the j^{th} feature of i^{th} training sample.

Here the cost function for this linear model is given by the equation

$$J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2 \qquad (5)$$

$y^{(i)}$ - Targets of the i^{th} training sample
m - Number of training samples

Training of the linear regression model is done using the gradient descent algorithm.

C. Gradient descent algorithm

In both the regression, we will use batch gradient descent algorithm to minimize the cost function $J(\theta)$.In this algorithm, iterations performed to update the θ_j by the following equation.

$$\theta_j = \theta_j - \alpha\frac{\partial J(\theta)}{\partial\theta_j} \qquad (6)$$

α- Learning rate.

$$\frac{\partial J(\theta)}{\partial\theta_j} = \frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})\, x_j^i \qquad (7)$$

The iterations are carried out until the values of θ_j i.e. parameters come closer to the optimum values by which low-cost function$J(\theta)$ is achieved.

As a result, of the training, the suitable defect depth (target) is assigned to each pixel. In the prediction mode, the vectors representing the temporal evolutions of temperature rise are applied to the model inputs and the corresponding target value is compared as per the algorithm. As a result of the prediction mode, the defect depth for every pixel in the field of view of the material is evaluated.

RESULTS OF DISCUSSIONS

In order to verify the proposed modality, the specimen is stimulated by a frequency-modulated optical stimulus of frequencies swept from 0.01 to 0.1Hz in a duration of 100s, from a set of halogen lamps of 1kW each a Figure-1.a. A cooled infrared, is placed at a distance of 1m opposite to the experimental carbon fibre reinforced plastic specimen containing embedded flat bottom holes (Figure-1.b), which captures the subsequent thermal response at a frame rate of 25 Hz.

The captured thermal history will be pre processed by employing linear fitting procedure and further processing is carried in classification followed by regression.

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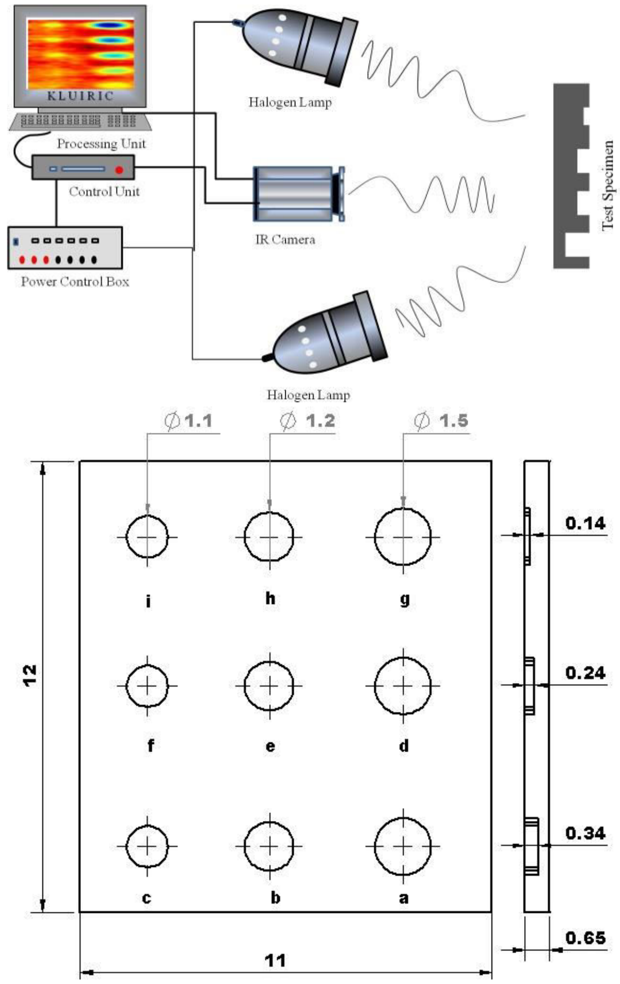

Figure-1.a. Experimental setup for active thermal wave imaging b. Layout CFRP specimen with side view.

Methodology of research

a) Mapping the thermograms sequence in the form of three-dimensional temperature matrix as (x, y, N) where x - the number of pixels in the field of view along the length, y - the number of pixels in the field of view along the width, N - the number of thermograms in sequence for the stimulated period of time.

b) Arranging the datasets given to the model in the training mode represents the sequences recorded in the experiments.

c) Developing the regression model. The number of inputs and outputs given to the model basing on the algorithm.

d) Training the logistic and linear regression model is done using gradient descent algorithm minimizing the cost function.

e) Simulation of the prediction is performed, the depth values thus obtained are noted and error values are recorded for further analysis.

f) Analysis of the recorded results.

A. Classification stage

The results of the classification stage, the first stage of the two-stage regression model used for or defect detection and characterization are presented in Figure-1.

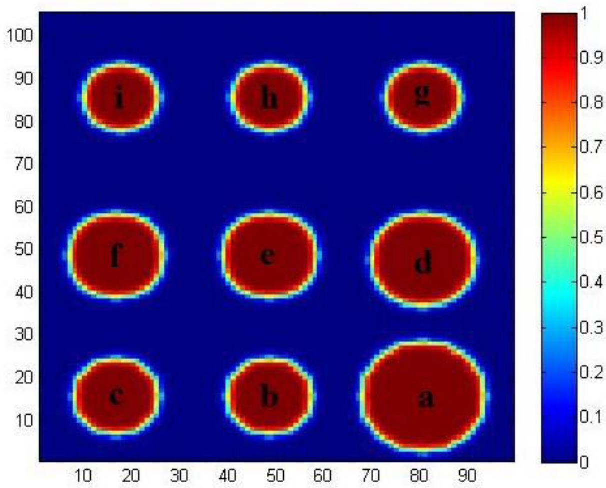

Figure-1. The map of defects' detection using the logistic regression trained with the HEAT dataset (classification stage).

Table-1. Classification errors obtained from the logistic regression stage.

Defect	Actual value	Estimated value	Error
a	1	1	0
b	1	1	0
c	1	1	0
d	0	0	0

Random pixel locationswere chosen to evaluate the error obtained from the classification stage. Here estimated value represents whether the location is categorized as defective or non-defective.

B. Regression stage

The results of the regression stage, the second stage of the two-stage regression model used for or defect detection and characterization are presented in Figure-2.

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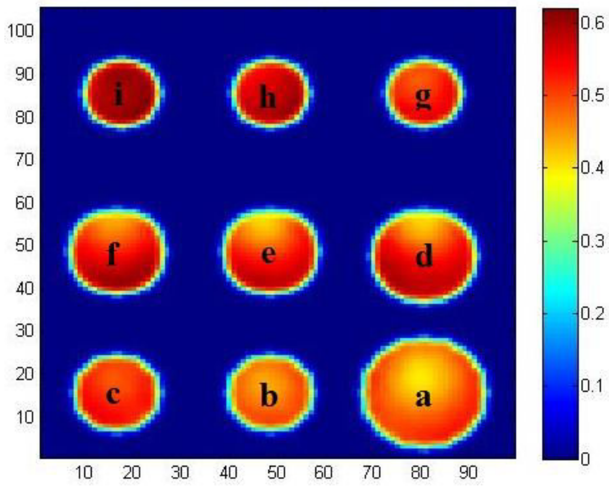

Figure-2. The map of defects' depth using the linear regression trained with the HEAT dataset (regression stage).

Table-2. Regression errors obtained from the linear regression stage.

Defect	**Depth** (mm)		**Error**
	Actual	**Estimated**	
g	0.51	0.5126	.0026
d	0.41	0.4112	.0012
a	0.31	0.3251	.0151
-	0.65	0.6507	.0007

Random pixel locations were chosen to evaluate the error obtained from the classification stage. Here estimated value represents the defect depth (one among the nine defect depth).

CONCLUSIONS

On the basis of the two-stage regression model following conclusions can be stated. As the primary insight of regression model is that it is dynamic and adjusts its parameters based on the input features for the corresponding targets. Results obtained from the two-stage regression model are close to the actual values which make it a good approach for quantitative and qualitative analysis.

In classification stage, the model is trained in a way such that it can detect the defect.

In regression stage the maximum error (0.0151) is obtained at the pixel location 'c' (79, 20) stated in Table-2 for the depth z = 0.31 mm.

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