Fuzzy Decision Tree Based Characterization of Subsurface Anomalies

A. Vijaya Lakshmi, V. S. Ghali

Abstract*: Recent intervention of machine learning based methodologies into infrared thermography proves to provide better defect detection and characterization. This paper provides a Fuzzy decision tree based quantitative post processing modality along with a theoretical model for thermal waves to characterize the subsurface anomalies using quadratic frequency modulated thermal wave imaging. A carbon fiber reinforced polymers (CFRP) and mild steel (MS) specimens having flat bottom holes with different depths and sizes are processed through experimental evaluation. A direct depth estimation is provided by the proposed modality being evaluated from the proposed mathematical model. In addition, its detection capability and reliability over other contemporary approaches is compared using signal to noise ratio, defect sizing and probability of defect detection.

Keywords*: Active Infrared thermography, Random projection, Fuzzy C-means clustering, Fuzzy decision tree and Quadratic frequency modulated thermal wave imaging.

I. INTRODUCTION

Early inspection through Non-destructive testing (NDT) of various anomalies facilitates to assess the integrity and strength of materials in industrial applications. Thermal wave imaging emerged as a well-grounded qualitative and quantitative approach to provide these requirements. Thermal contrast over surface of an object under a controlled stimulus is analysed for defect characterization in active thermography (AT). Various processing schemes proposed on this thermographic data for defect detection and characterization. Application of machine learning based approaches in addition to signal processing makes it feasible to minimize human intervention and provides precise decisions. This will improve the authenticity of anomaly detection and furtherance for better characterization of structures as well. Literature [1] assures the credibility of these approaches in enhancing the quality of testing procedures and to overcome a few analysis predicaments through human intervention in NDT.

Conventionally, pulse [2, 4-5] and lock-in stimulations [3] are famous stimulation mechanisms but these techniques limited by their high peak power stimulus and repeated experimentation respectively [3-5]. To overcome these limitations and to provide adequate defect depth resolution, Non-stationary thermal wave imaging systems have been introduced which uses moderate peak power optical stimulus modulated by a band of low frequencies [6-8]. Linear frequency modulation [6] and quadratic frequency modulated [7-8] stimulations are two varieties this NSTWI systems where QFMTWI probes more energy into the object at low frequencies compared to its linear counterpart. On the acquired thermal response, variety of signal processing techniques employed for qualitative and quantitative characterization of the defects.

Fuzzy decision trees (FDT) is a machine learning tool for decision making provides a set of graphical structure of tree [9-11]. In this predict the target variable value from input attributes. The three conventional steps in Fuzzy decision tree are i. Feature extraction and dimensionality reduction, ii. Fuzzification followed by Classification. The features correspond to a signal might be time domain, frequency domain or statistical measures. Feature extraction and dimensionality reduction results in uncertainty in the data which produce errors in expected results [9]. Fuzzification is the process of converting these low dimensional features into fuzzy data sets to avoid the uncertainty. Then a FDT is employed to classify the signal.

In present work, a mild steel specimen and a CFRP specimen with different sizes of flat bottom holes at various depths is excited with Quadratic frequency modulated heat flux and the observed thermal response is linear fitted for extracting only dynamic component of the thermal response. To this thermal response, FFT phase, Pulse compression [12] and proposing Fuzzy decision Tree classifier is employed. In Fuzzy decision tree, feature extraction and dimensionality reduction is carried out by random projection transform [13] and Fuzzification is performed by fuzzy c means clustering and to that FDT is employed on the fuzzy data set for defect classification and depth prediction. Further, a qualitative measure of detection is provided between afore mentioned and proposed methodology through defect SNR, sizing and probability of detection [8].

Paper organized as, section II discusses about QFMTWI followed by conventional and fuzzy decision tree methodologies in section III. The subsequent observations and their discussions given in section IV and finally article concluded in section V.

II. QFMTWI

The quadratic chirped stimulus is given by [7-8]

$$H(t)=H_0 \sin(a\,t+b\,t^3) \tag{1}$$

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Here the stimulus initial frequency as ‘a’, bandwidth ‘b’ and intensity of heat flux ‘H_0’. The 1D heat diffusion is given by

$$\frac{\partial^2 T\ (x,t)}{\partial T^2} = \frac{1}{\alpha}\frac{\partial T(x,t)}{\partial t} \quad (2)$$

Here thermal diffusivity of the material is represented by ‘α’ and solving eqn. 2 imposing eqn. 1 using boundary conditions of the sample is given by

$$-k\frac{\partial T}{\partial Z}\Big|_{x=0} = Q_0 e^{j2\pi\left(a+bt^2\right)t} \quad (3)$$

Here thermal conductivity of the material represented by ‘k’ is and amplitude of heat flux represented by ‘Q_0’. With solution of equation (2) one can obtain the diffusion length ‘δ’ as:

$$\delta \propto \sqrt{\frac{\alpha}{1.77(a+bt^2)}} \quad (4)$$

By the equation (4), the QFM stimulus provides depth resolution. And phase at any location is given by [10]:

$$\phi_r = -\frac{3\pi}{4} - \sqrt{\frac{2\theta}{\alpha t}}d + \phi + \phi_1 - \frac{\theta\sqrt{\theta}}{\sqrt{6bt^3}} \quad (5)$$

It is clear that obtained phase value can be used to estimate the characteristics of the anomaly. Here polar coordinate system parameter is represented by ‘θ’ are the. So the equation (5) represents the depth (d) of the defect is proportional to corresponding phase which is used to estimation of defect depth.

III. PROCESSING OF THERMAL RESPONSE

Subsurface features of object is obtained from analyzing recorded thermal response with the aid of suitable conventional signal processing approaches and the proposed fuzzy decision tree based modality for enhanced defect visualization. The thermographic processing approach based on fuzzy decision tree [9-11] is represented in Fig.1.

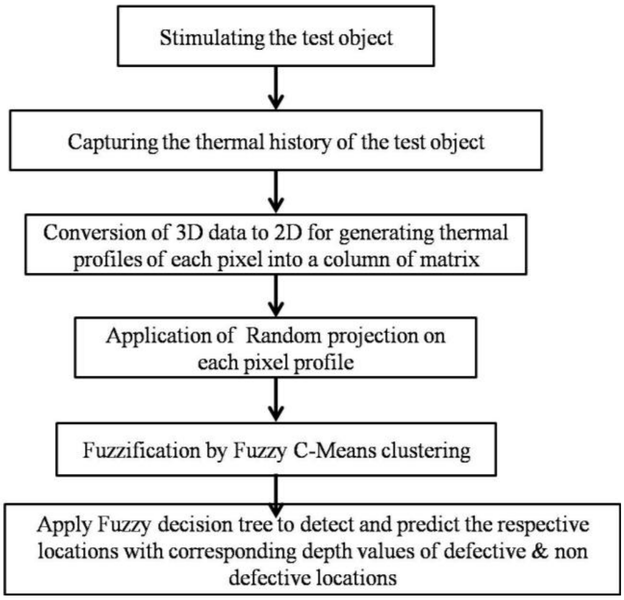

Fig.1. Fuzzy Decision tree based thermographic processing approach

A. FFT Phase

The proposing modality is compared with two conventional processing techniques over which FFT phase is a frequency domain phase approach, phase contrast between non-defective and defective counterparts obtained by corresponding phase delay between thermal profiles.

B. Pulse compression

Since FFT underestimates the sub-harmonics of low frequency chirped thermal response which is responsible for defect depth resolution, a time domain cross correlation approach is recommended to cater this limitation. In this approach a reference thermal profile is used to cross correlate with each thermal response and peak delays used for defect depth quantification.

C. Fuzzy Decision tree

After collecting of thermal data from infrared imager, the random projection is a method used to separate noise from this data and provides better subsurface details. RPT results in orthonormal projected dataset which separates non-uniform radiation, noise [13] and reduces the dimensions of the data which enhance the detectability. Dimensionality reduction results in information loss or spatial or temporal uncertainty in the data which can be overcome by Fuzzification.

In this work fuzzification can be done by Fuzzy C-means clustering algorithm (FCM) [9-10]. Assume the j^{th} attribute Y_j as changed into set of membership terms n_j. Fuzzy C-means algorithm used to split the scalar values y_p into n_j clusters with different membership values $u_{p,i}$. The minimization of objective function with FCM algorithm as:

$$\sum_{p=1}^{P}\sum_{i=1}^{n_j}(u_{p,i})^2 d(y_p, c_i)^2 \quad (6)$$

Where d (y_p,c_i) is maximum space between y_p and ci of j^{th} cluster.

Fuzzy decision tree (FDT) is a tree like structure for decision support used for prediction of target variables. Fuzzy decision tree consists of decision nodes and leaves. Input of each node is a fuzzy attribute with two outgoing branches. It consists of intermediate nodes to perform the test on input variables and terminal nodes indicating the labels of class. The tree is constructed with growing tree process and splitting points. It tests all given variables with possible splits and the best maximizes the drop in the node impurity. This paper employs the fuzzy decision tree algorithm for detection and characterization of defects from captured thermal response of QFM stimulated experimental specimen. The fuzzy decision tree classifier assigns a class to each pixel During training period fuzzification profiles are used for training purpose with duration of 123sec with 16GB RAM, 512GB SSD and intel7 machine. The fuzzy decision tree provides to predict the depth values for each pixel.

IV. EXPERIMENTATION AND PROCESSING

To test the projected methods, conducting experimentation on Mild steel (MS) sample and Carbon fiber reinforced plastic (CFRP) with back holes at various depths and sizes are shown in Fig.3.

The samples are energized by a QFM heat flux with sweep frequency of 0.01-0.1 Hz with for 100s by a set of 1kW power halogen lamps each. Thermal response captured at 0.04 frames per second by an infrared camera.

Subsurface details can be extracted by preprocessing the each thermal profile using linear fitting procedure and further deploying the suitable post processing approach like FFT based phase, pulse compression and Fuzzy decision tree based approach over the dynamic thermal response. Active thermography experimentation setup is illustrated in Fig. 2

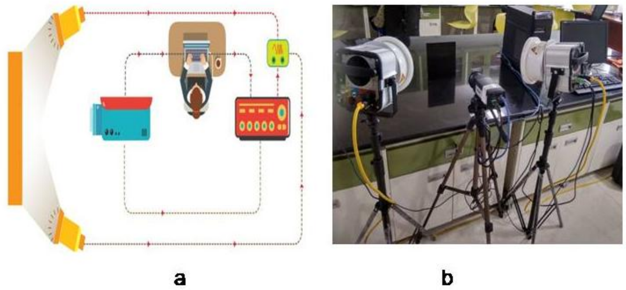

Fig.2.a. Schematic view b. experimental setup of active thermal wave imaging system

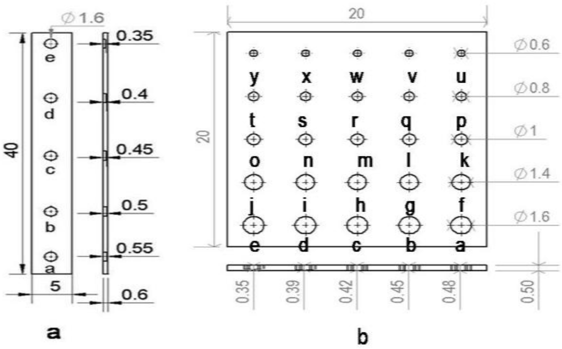

Fig.3. Layouts of a. Mild steel specimen b. CFRP specimen layouts

Fig.4 represents subsurface details of Mild steel specimen and Fig.5 represents the subsurface details of CFRP sample. Fuzzy Decision tree provides the subsurface anomalies with better contrast than contemporary processing approaches in both the cases are found to be useful for thermographic studies. The quantitative depth estimation provided by fuzzy decision tree is observed in respective thermograms.

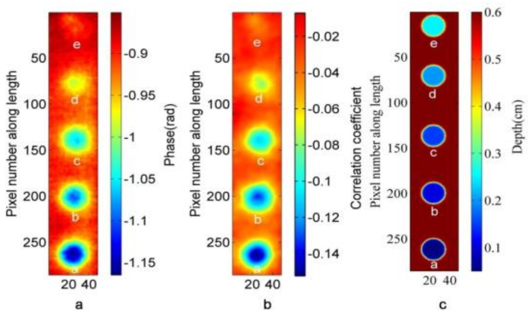

Fig.4.a. FFT Phase b. Pulse compression c. Fuzzy Decision tree

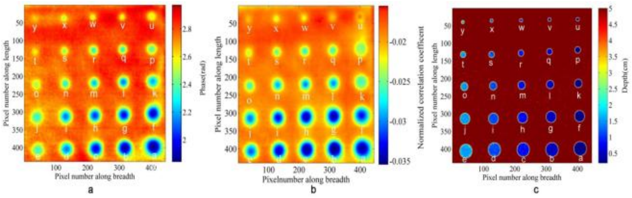

Fig.5.a. FFT Phase b. Pulse compression c. Fuzzy Decision tree

Signal to noise ratio (SNR) as given in eqn. 9 is used as primary quantification measure for quality of various contemporary processing approaches and obtained SNRs presented in Fig.6 for mild steel sample and Fig.7 for CFRP sample. It clearly resembles that fuzzy decision tree is performing better compared to other processing approaches.

$$SNR(dB) = 20\log\left(\frac{\mu_{Defective} - \mu_{Non-Defective}}{\sigma_{Non-defective}}\right) \tag{9}$$

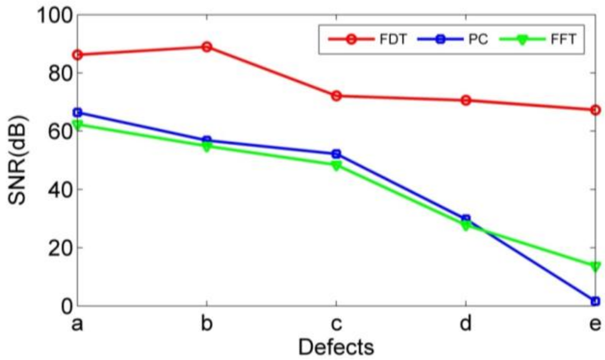

Fig.6. Detectability of defects for Mild steel sample

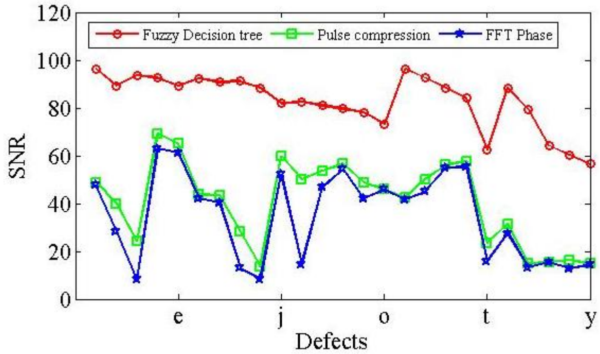

Fig.7. Detectability of defects for CFRP sample

A.Defect sizing

Size estimation plays vital role in infrared thermography in order to recommend the component for repair, reuse or to replace. Table.1. represents the sizing of different defects in CFRP sample with flat bottom holes for various methods. Table.1 illustrates that the defect size calculation, from these decision tree closely resembles the actual size of the defect.

Table1. Defect size estimation of CFRP sample

Defect	Full width at half maxima(in cm)				
	a	f	k	p	u
Real size	1.6	1.4	1	0.6	0.3
Decision tree	1.61	1.43	1.14	0.63	0.33
Pulse compression	1.81	1.45	1.36	0.71	0.35
FFT Phase	1.55	1.19	0.90	0.77	0.51

B. Probability of detection

Reliability of defect detection in the proposed modality has been assessed with the probability of detection (POD) [8] using the experimental CFRP sample. This probability estimation along with the aspect ratio for different processing methods like decision tree, pulse compression and phase analysis are represented in Fig.8. The POD of the projected method presents best reliability as compared to the other processing methods even for defects having very smallest aspect ratio.

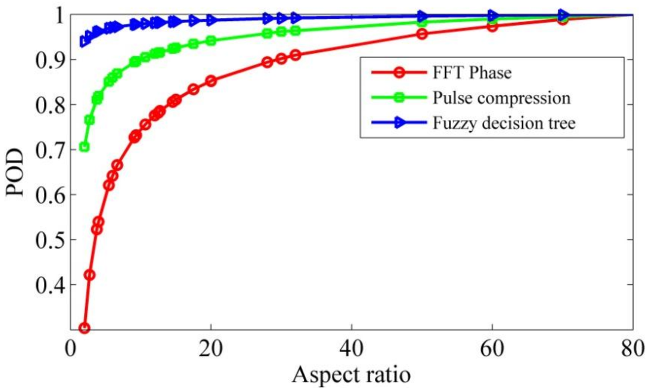

Fig.8. POD curve for various post processing methods

V. CONCLUSION

A Fuzzy decision tree based detection and characterization of subsurface defects anomalies analysis is employed on QFMTWI for experimental mild steel and carbon fiber reinforced plastic specimens. The ability of the fuzzy decision tree approach has been verified experimentally and validated for defect detection by taking SNR of defects into consideration and sizing estimation has been done using full width at half maxima analysis and reliability using probability of defect detection. It is concluded that, proposed fuzzy decision tree provides better defect detection along with depth quantification.

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