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A Machine Learning based Approach for Defect Detection and Characterization in Non-Linear Frequency Modulated Thermal Wave Imaging

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ABSTRACT

A machine learning based discrimination modality has been proposed for non stationary signal analysis to be used for sub surface characterization. This proposed modality improves the testability, reliability and present best detection in terms of quantified characteristics pertaining to anomalies. In this paper the region based active contour segmentation along with artificial neural network (ANN) has been employed to facilitate the practitioner in assessing the quality of the test body. The present study carried out over a numerically tested biomedical bone sample with different density variations to simulate Osteoporosis and an experimental Carbon fiber reinforced composite specimen. The performance of the proposed methodology compared with conventional signal processing techniques pertaining to the aspects of defect signal to noise ratio, probability of defect detection and concluded that ANN and Decision tree based processing modalities provide better characterization.

Key words : Quadratic frequency modulated thermal wave imaging, Artificial neural network, Decision tree, Bone, CFRP, Pulse compression, Time domain phase.

1. INTRODUCTION

Data exploration and analysis are playing a vital role in recent past. Machine learning modalities are facilitating in arriving at easiest and quick conclusion for analysts. Machine learning is a sub branch of Artificial intelligence provides solution to a problem with efficiently. Machine learning techniques are extensively used in signal processing, pattern recognition, speech recognition etc [1, 2]. Active infrared thermography is a non-contact, whole field; non-destructive testing modality used in various industries for quality evaluation of objects which results in a dataset of thermogram sequence [3]. This data set is generated by applying a controlled stimulus on to the object and corresponding thermal contrast created by subsurface defects and reflected thermal waves from them is captured by an infrared camera. Varieties of optical excitation schemes are available such as short duration, high peak power pulse excitation (PT) [4-5], moderated peak power periodic excitation (LIT) [6-7] and a band of low frequency modulated excitation named as Non-stationary excitation techniques (NSTWI) [8-10]. Effect of heat radiation and heat transfer has been analyzed in various domains [25, 26]. Recent advancements of active infrared thermography make use of these NSTWI techniques which will provide deeper depth scanning of objects compared to conventional PT and LIT.

In general, variety of signal and image processing schemes [11-15] applied on observed thermal response to validate defect detection, depth quantification and material property estimation etc., But in present scenario where artificial intelligence and machine learning is ruling the world, these signal processing and manual inspection based modalities lags the performance, quality and time as well. To overcome with such cases and to be synchronized with present scenario of the world, machine learning techniques are utilized to detect and characterize the anomalies placed in materials [16, 17, 19]. Unsupervised classifiers like KNN and fuzzy c means provide better defect detection in QFMTWI [24]. Whereas, Decision tree (DT) and artificial neural networks (ANN) is supervised machine learning algorithms used to predicting similar information from the categorical class variable. In this work, these supervised machine learning algorithms are applied to temporal thermal response of materials collected from infrared imager in supervised learning entire data can be dividing into testing and training datasets. Once prepare these data sets, we can use it for test the new data for feature information [16, 19].

From few decades artificial neural networks are used to solve the non-linear problems, because of powerful and adaptive tool for classification and prediction [1, 16-18]. ANN is used to detect and predict the anomalies in thermal nondestructive evaluation. A feed forward back propagation multilayer perceptrons were applied over the temporal thermal response of each pixel extracted from QFMTWI. The network inputs are preprocessed temporal thermal response of each pixel and network output shows non-defect and defect category and also estimate depth of corresponding pixels.

Decision tree is a supervised machine learning algorithm used for classification and regression tasks; it is tree like structure consists of branches and nodes. Every node represents corresponding attribute value and each branch represents a value corresponding to that node. Classification and regression tree (CART) is one of the algorithm used to build both regression and classification trees. Each node selects best attribute and split the training set into subsets until the leaf nodes are generated. The process results in a partition of the learning sample into smaller subsets [2, 19-20].

In this paper machine learning techniques like ANN and decision tree are employed on thermal response acquired from numerically simulated bone sample [21] with different density variations and experimentally evaluated CFRP sample. Both the samples are excited by quadratic frequency modulated heat flux [10]. The proposing methodologies are compared with contemporary signal processing methods like Pulse compression, Hilbert phase and FFT phase. Further active contour based image segmentation is employed for localizing the defects accurately [22].

2. QFMTWI

Heat diffusion in an object is mathematically analysed through solving homogeneous differential equation for 1D heat diffusion. In case of bio medical system, general bio heat transfer equation considering all the arterial, Venus blood vessels, skin, fat and bone is that is widely used Penne's bio-heat transfer equation given by [21]:

$$(\rho c)_{tissue}\frac{\partial T}{\partial t} = k_{tissue}\frac{\partial^2 T}{\partial x^2} + (\rho c)_{blood}\, w(T_{core} - T) + Q_{metabolism} \quad (1)$$

Since the present work omits the considerations of blood perfusion w, temperature difference between core and arterial blood vessels, and the metabolism then the second and third terms in above equation tends to be zero. Then the bio-heat transfer equation modified to be general heat transfer equation with tissue thermal properties as:

$$(\rho c)_{tissue}\frac{\partial T}{\partial t} = k_{tissue}\frac{\partial^2 T}{\partial x^2} \quad (2)$$

Can be represented as

$$\frac{\partial T^2}{\partial x^2} = \frac{1}{\alpha}\frac{\partial T}{\partial t} \quad (3)$$

Where temperature located at point 'X' indicated by T(x, t) and thermal diffusivity of material represented by 'α'. The object surface excited by a quadratic chirped stimulation as [10]:

$$H(t)=H_0\, e^{(a\,t + b\,t^3)} \quad (4)$$

Where, 'a, b' is starting frequency and bandwidth of the stimulus with intensity 'H_0'. At the top of specimens surface heat flux produces and is represented by:

$$-k\left.\frac{\partial T}{\partial Z}\right|_{z=0} = Q_0 e^{j2\pi\left(a+bt^2\right)t} \quad (5)$$

Where 'k' is thermal conductivity of material and 'Q_0' is heat flux. By solving equation (3) the diffusion length is represented as:

$$\delta \propto \sqrt{\frac{\alpha}{1.77(a+bt^2)}} \quad (6)$$

With equation (6), it clears QFMTWI provides depth resolution with respect to time varying frequency. The phase at any location is represented by [19]:

$$\phi_r = -\frac{3\pi}{4} - \sqrt{\frac{2\theta}{\alpha t}}d + \phi + \phi_1 - \frac{\theta\sqrt{\theta}}{\sqrt{6bt^3}} \quad (7)$$

Further, the depth quantification is provided by this proportional relation between phase and defect depth as given in eqn. 7.

3. POST PROCESSING METHODS

Optical excitation produces heat up the sample surface and further these heat waves diffuse into subsurface layers. A thermal contrast created over the sample surface due to the reflected thermal waves from subsurface anomalies. The observed thermal response composed of stationary and dynamic thermal variations. To acquire dynamic response pre-processing the data using linear fitting method is carried out and machine learning based post processing approaches are employed for quantitative visualization of subsurface features as shown in Figure 1. Along with proposed methodologies, other conventional methods like FFT based phase, Pulse compression and Hilbert phase analysis are employed.

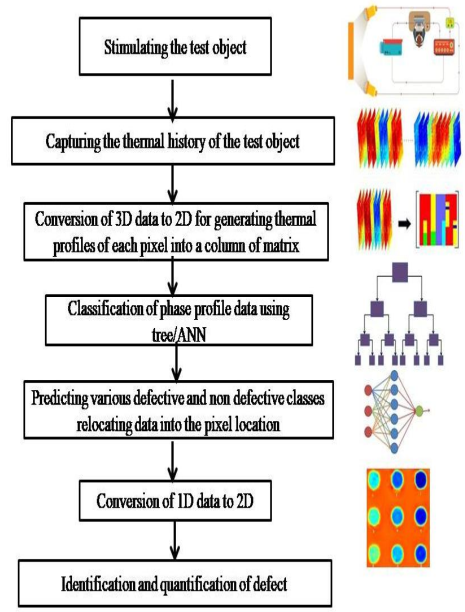

Figure.1: Thermographic processing for subsurface analysis

3.1 Phase analysis using FFT

A conventional processing modality in which the thermal response is analysed in frequency domain by computing Fourier transform on it. From the complex values, phase value is computed which results in a thermal contrast with respective phase differences between defective and non-defective regions in phasegram [10].

3.2 Time domain phase analysis using Hilbert phase

A multi transform technique in which the thermal response is convolved in frequency domain with a Hilbert transformed reference profile which further results in correlation and time domain phases. Further defect depth quantification is analyzed from these phasegrams [13].

3.3 Pulse compression

Applying cross correlation between mean removed thermal response and a reference profile results in correlation sequence with peak delays respective to defects at different depths to its non-defective counterpart. This is a time domain approach [11].

3.4 Artificial Neural Network based analysis

Artificial Neural Networks (ANN) is large number of highly interconnected parallel processer used to solve complex problems [1, 16-18]. To provide subsurface anomaly detection and characterization AAN has been proposed in this paper.

The temperature profiles information applied to input layer and the respective classification results is collected at output layer using input membership functions and allied parameters through output membership function.

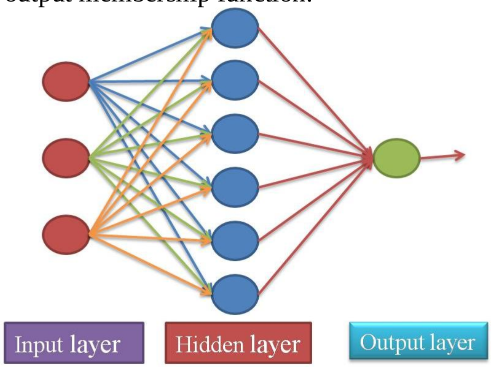

Figure 2: Neural network for estimation of defect

In this work a multilayer perceptron employs through 100 inputs nodes and 20 hidden nodes for training and investigation and the target as defective or non-defective is provided by output node as illustrated in Figure 2. The recognition and estimation of anomalies is performed by tan sigmoid activation function with back propagation algorithm.

3.5 Decision Tree

Decision tree is a nonparametric modality used for classification as well as regression tasks [2, 19-20] based on tree based structure. Classification and Regression Tree (CART) is one such binary tree having nodes with children nodes each at the output. To indicate class labels we have an intermediate node in the children nodes. By using greedy algorithm the splitting points are selected. It tests all given variables with possible splits and the best maximizes the drop in the node impurity using Gini cost function to indicate the purity of the nodes using:

$$g(k) = \sum_{i=1}^{J} p(i) * (1 - p(i)) \qquad (8)$$

Where *p(i)* is probability of detection of node k.

This paper deploys the decision tree algorithm for detection and characterization of defects from captured thermal response of QFM Stimulated experimental specimen in two successive steps namely classification for detection and regression for depth estimation corresponding to each pixel in view. During regression process, training vectors are created corresponding to each profile and applied to the input for suitable depth assignment which can be used further to predict the target variables by learning decision rules.

4. MATERIALS AND EXPERIMENTATION

To support the proposed modalities, thermographic data extracted from numerical simulation of bone sample resembling a case of reduced bone strength due to aging in humans and experimental CFRP sample with flat bottom holes. Bone sample composed of various layers like skin muscle and fat of 0.5mm each and a bone of 2.5mm thickness with 7-2cm size holes with different density variations. Schematic layouts of samples are shown in figure 3. a and b respectively. The thermal properties of sample are referred from [21].

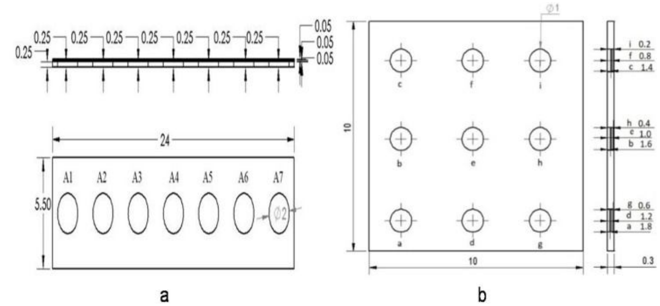

Figure 3:.Layout of modeled a. bone sample and b. CFRP sample

A schematic of experimental setup for QFMTWI is given in figure 4. The excitation is provided with a frequency sweep of 0.01Hz to 0.1Hz for 100 seconds and corresponding thermal response is observed at a frame per 0.04secs. Obtained thermal response is linear fitted and mean removed to get the dynamic thermal response. Further various processing schemes have been employed on the thermal response.

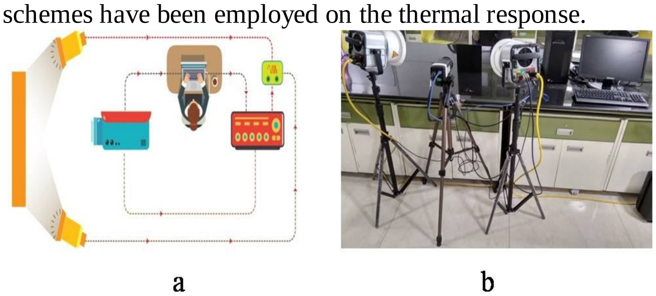

Figure.4 :a. Schematic view b. experimental setup of active thermal wave imaging system

5. RESULTS AND DISCUSSION

The corresponding results obtained from machine learning approaches like Decision tree (DT), artificial neural networks (ANN) are compared with the signal processing method like Pulse compression (PC), Hilbert phase (HP) and FFT Phase (FFT) in Figure 5 and Fig.6 for Bone and CFRP samples respectively. Among these outputs, decision tree classifier exhibiting every defect with deepest depths also with good contrast.

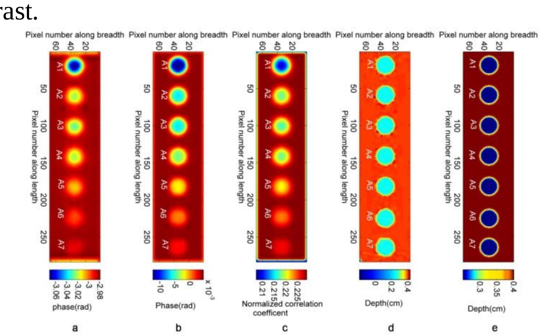

Figure 5:. a. FFT Phase b. Hilbert Phase c. Pulse Compression d. Artificial Neural Networks e. Decision tree for Bone sample Artificial Neural Networks e. Decision tree for CFRP sample

Signal to noise ratio is a basic measure of quality in various signal and image processing techniques. Here SNR is calculated by mean (μ) and standard deviations (σ) of defective and non-defective regions as given below

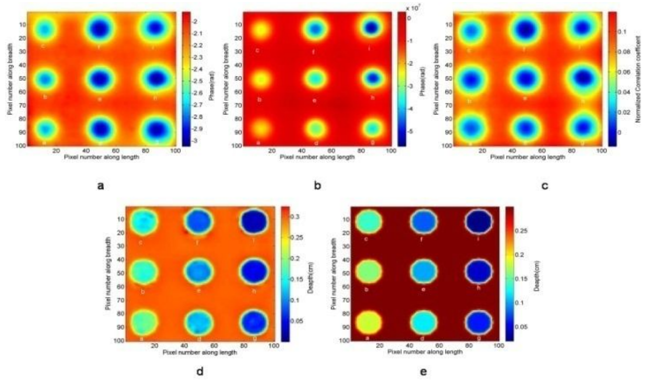

Figure 6:. a. FFT Phase b. Hilbert Phase c. Pulse Compression d.

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

SNR is computed for all defects in bone and CFRP samples and obtained good SNR of decision tree and ANN compared conventional signal processing schemes which is given in below figure 7 a and b respectively.

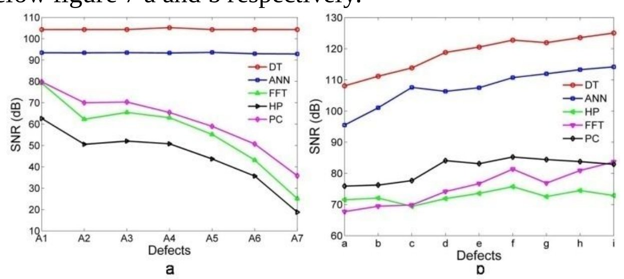

Figure.7:. a. SNR of defects for Bone sample and b. SNR of defects for CFRP sample

Full width at half maxima (FWHM) is a defect sizing method in infrared thermography. Processing thermal sequence with various methods will effect in spatial resolution further mislead in estimating exact defect size. Here, the application of machine learning techniques analysed with defect size estimation through FWHM and obtained estimated sizes is given in below table.1 for bone specimen.

Table1: Defect size estimation for Bone sample

Defect	Actual Size (cm)	Estimated Size (cm)				
		DT	***ANN***	***PC***	***HP***	***FFT***
A1	2	1.96	1.93	1.84	1.82	1.80
A2	2	1.97	1.95	1.76	1.82	1.76
A3	2	1.96	1.95	1.77	1.79	1.79
A4	2	1.97	1.95	1.87	1.82	1.80
A5	2	1.97	1.94	1.87	1.83	1.79
A6	2	1.96	1.93	1.85	1.82	1.78
A7	2	1.97	1.93	1.79	1.77	1.78

Reliability of defect detection in the proposed modality has been assessed by probability of detection (POD) [23] 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 Figure 8. It is observed that POD of the proposed method presents best probability of detection as compared to the other processing methods even for defects of smallest aspect ratio.

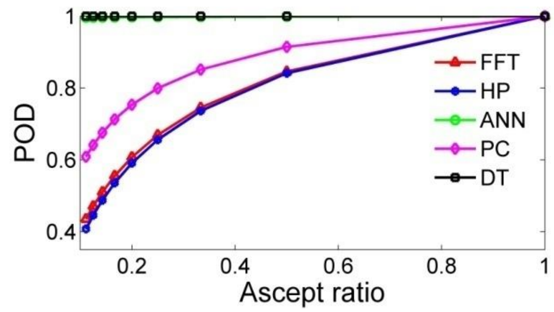

Figure 8:. Probability of defect detection curve for different processing methods

Further, Region based active contour image segmentation is performed based on the statistical modeling of image [22]. To segment the objects accurately, an active contour energies considered with local information with utilization of region based segmentation techniques. To set the initial contour of zero level set function, the foreground and background based on their mean intensity levels.

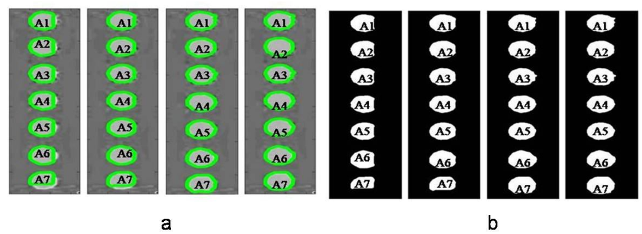

Figure 9: Contour (left) and segmented (right) images of Bone sample with 20, 50, 100 and 150 iterations respectively for ANN output.

Then expand the contour, and mean intensities of background and foreground have maximum difference. It makes the curve on global constraints along the boundary of foreground. In this paper, the active contour image segmentation applied to results obtained from the artificial neural networks from Fig.5d with 150 iterations and corresponding segmented results are illustrated in Figure 9.

6. CONCLUSION

In this paper, the capabilities of ANN and decision tree based supervised machine learning modalities are tested on thermal response acquired from QFMTWI of a numerically simulated bone sample with density variations and experimental CFRP sample with flat bottom holes. The proposed methodologies are compared with conventional processing schemes and from the qualitative comparison of signal to noise ratio, defect sizing and probability of defect detection, it is concluded that machine learning based technique provide better results.

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