ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 1, 2019

Enhancing Defect Detection Principal Component Analysis in Quantitative Non-Stationary Thermal Wave Imaging

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Abstract.

Active thermography has been emerging as a reliable non-destructive testing method due to its whole field, non-contact and non-invasive evaluation capability. It uses the acquired history of surface infrared emission over the object and subsequently obtains subsurface details. But faint contrast detail accompanied with spurious data generated in experimentation leads to false interpretations with raw data analysis. A suitable processing, which enhances the signal to noise ratio and un-correlate noise by separating the noise from other features facilitates enhanced detail extraction. Either pulse compression or feature separation methods accomplish this task and improve the potential defect detection performance.

In this paper introduces various feature separation methods and investigates their enhanced defect detection performance than existing conventional processing methods in Infrared imaging for non- stationary thermal wav e imaging methods. a correction has been made to the theory of thermal waves generated with Quadratic Frequency modulated thermal wave imaging (QFMTWI) and in the next stage various processing methods have been tested for captured thermographic data generated during QFMTWI with a goal of exploring fine subsurface details. Finally features of various processing methods have been compared from defect visualization perspective.

Keywords: Defect detection, Principal Component Analysis (PCA), Quantitative Non-Stationary Thermal Wave Imaging, Non-destructive testing Thermal wave analysis, Anomaly identification

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1.Introduction

Several researchers have been intrigued by the high quality and defect-free materials of recent decades, leading to their possible uses in a various application, such as aerospace, mechanical and civil engineering. If the material has any defects, such as delimitations, flaws and voids during the manufacturing stage which reduce their in-service applications [1]. Among various non-destructive evaluation (NDE) techniques, Active Infrared thermography has been emerging as a reliable non-destructive testing method because of its non-contact, non-invasive and whole field evaluation method.

In active thermography, employs a controlled external stimulation to extract subsurface details with good contrast and thermal response is observed on surface of sample. The active thermography can be categorized depending upon applied stimulus as Pulsed thermography (PT) [2], Lock-in Thermography (LT) [3], Pulse Phased Thermography (PPT) [4]. In PT, employs a short duration high peak power source from flash lamp applied to surface of test object and corresponding temporal thermal response can be captured by using infrared imager. But, use of high peak power remains a major drawback. In LT, a continuous low power periodic stimulation is applied over surface of test object; the thermal response is captured by Infrared imager. The selection of suitable frequency and repetitive experimentation requires the defect location at different depths and consumes more time. In PPT, applies pulse based energy for stimulation and phase based analysis for defect detection. Experimentation is same like PT, but analysis is carried by application of Fast Fourier Transform (FFT). Frequency modulated thermal wave imaging (FMTWI) are introduced recently to overcome the problems of conventional methods. In FMTWI [5, 6] a suitable band of frequency will be applied to test object within a single experimentation, which will probes the entire sample within a single experimentation. Quadratic frequency modulated thermal wave imaging (QFMTWI) [7-15] provide improved energy at low frequencies and provides deeper depth analysis.

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2.Methodology

In Infrared Non-Destructive Testing (IRNDT), the surface of the test sample is exposed to a quadratic frequency-modulated optical stimulus. This stimulus initiates similar thermal waves in a very thin layer close to the surface, which then propagate into the object's interior through diffusion wave propagation. As a result, it creates a temperature contrast on the object's surface, highlighting subsurface anomalies. To extract fine details from beneath the surface, the captured thermal data undergoes various processing methods. These include phase analysis, pulse compression, Hilbert phase analysis, Principal Component Analysis, and Random Projection processing methods. These methods are applied with the aim of defect detection using the recently introduced Quadratic Frequency Modulated Thermal Wave Imaging technique.

2.1 Phase analysis

This is a frequency domain method of analysis in which FFT has been applied over thermal profiles of each pixel and phase values corresponding to each frequency component is obtained. Further phasegrams were constructed from the phase value at a particular frequency component of all the pixels arranged in their respective locations. Phase contrast in these phasegrams can be used to visualize the defects. As the frequency of the phasegram is equal to the corresponding frequency of the samples in their respective phase profiles obtained from Fast Fourier Transform estimations, given by

$$f = \frac{F_S \, n}{N},$$

Where F_S = Sampling frequency or capturing rate.

N = Total number of the samples in the thermal profile.

n = Number of the phasegram.

2.2 Pulse compression analysis

Pulse compression is a time domain method of analysis. In this approach, data of a pixel in captured thermograms is arranged in a sequence called temporal thermal profile of that pixel. A similar procedure is repeated with all the pixels in view and corresponding thermal profiles of all the pixels are generated. These profiles include temporal thermal response

ISSN PRINT 2319 1775 Online 2320 7876

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corresponding to offset in excitation and the dynamic response according to the proposed excitation. In order to obtain the corresponding dynamic response only (as shown in Fig.), the offset is removed from each profile using a suitable data fitting procedure (in general a linear fitting procedure is to be adopted). A reference profile is generated by taking the average of a few randomly selected mean removed non defective pixel profiles. In the next stage, a cross correlation is carried between the mean removed thermal profiles of all the pixels in view and the reference profile. This cross correlation of each pixel's profile results in a corresponding normalized correlation data sequence. A similar correlation profiles are computed for all the pixels profiles in view. These profiles were rearranged so that the normalized correlation coefficients of all the pixels at a delayed instant are kept in their respective spatial locations to form correlation image at that delayed instant. As shown in figure 3.5, they can provide a localized variation at defect locations due to their dependency on delay and attenuation corresponding to the defect profiles. This coefficient contrast in correlation images has been used to detect defects.

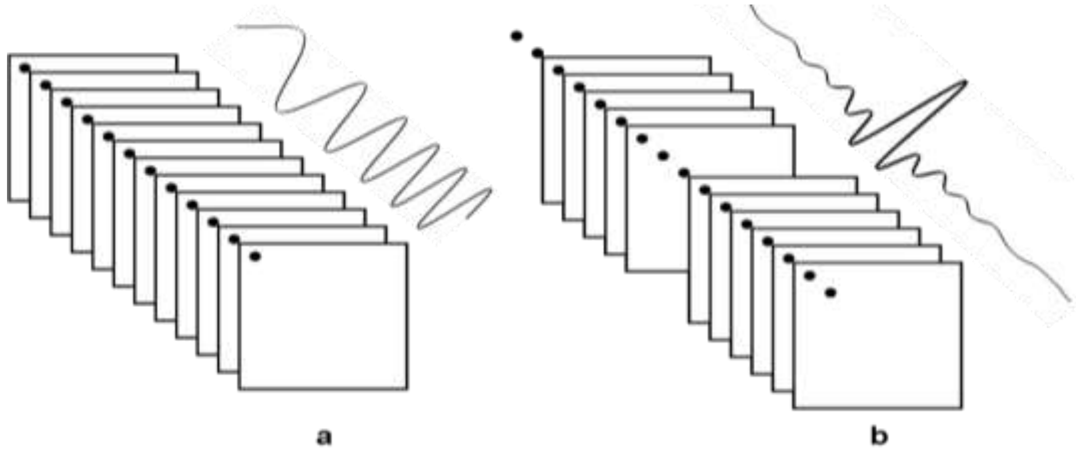

Figure 2.1.a. Thermogram sequence (n thermograms) **Figure 2.1.b.** Processed correlation image sequence (2 n - 1 correlation images).

This defect detection procedure is like thermogram study of PT in time domain. But noise removal while processing and improvement of SNR are the additional advantages gained with this approach in FMTWI.

In addition to these two methods, Tabatabei and Mandelies [68] make use of the time delay between the peaks of the correlation profiles for defect visualization. This method offers better detectability in case of thin samples (due to the delay obtained is more) or responses

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captured at high frame rates. Capturing the response at high frame rates produces a better time resolution (as sample number increases) to discriminate correlation peaks, which subsequently better resolve the defective and non-defective locations. In addition, shallower defects providing more delay than the deeper ones, enhances their detectability in this approach.

2.3 Principal component analysis for thermography

Principal component analysis (PCA) can be defined as the orthogonal projection of the data on to a lower dimensional linear space known as the principal subspace such that the variance of the projected data is maximized.

The PCA is a linear projection technique for converting a matrix A of the dimension m by q to the matrix Ap of the lower dimension s by q (s < m) by projecting A on to new set of principal axis. This can be done by the matrix multiplication.

$$A_p = u^T * A$$

where the columns of U are the projection vectors that maximize the variance retained in the projected data Ap. This operation can be also seen as a linear transformation that minimizes the reconstruction error or a procedure to obtain uncorrelated projected distributions. Each principal axis corresponds to the normalized orthogonal eigenvector of the scatter matrix

$$S = (A - A_{mean})(A - A_{mean})^T$$

of m by m elements. One simple approach to the PCA is to use singular value decomposition (SVD) of S:

$$S = \begin{pmatrix} u_s & u_n \end{pmatrix} \begin{pmatrix} d_s & d_n \end{pmatrix} \begin{pmatrix} u_s & u_n \end{pmatrix}^T$$

where U is the eigenvector matrix (i.e. modal matrix)and D is the diagonal matrix whose diagonal elements correspond to the eigen values of S (in descending order). Then the PCA transformation from m-dimensional data to s-dimensional subspace is given by choosing the first s column vectors. The matrix A_p taking into account the first s principal components is given

$$A_p = u^T * A$$

the captured data is in three dimensional for performing principal component analysis, a pre processing work on 3D data is required for setting a convenient way for singular value

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decomposition, i.e we convert the original captured 3D data into a two dimensional matrix A in such a way that the by arranging the time variations in row wise and the spatial variations along column wise

To make the PCA work properly,a covariance matrix for the above 2D matrix A is constructed by multiplying the mean removal matrix and its transpose. Now this scatter matrix is convenient for performing singular value decomposition. After applying SVD to the scatter matrix it decomposes 'S' in to three matrices which are Eigen vector matrix, diagonal matrix and transpose of Eigen vector matrix

The time variations have been obtained as columns in eigen vector matrix and the eigen values as diagonal elements in diagonal matrix and spatial variations as columns in third matrix. The principal components are determined by multiplying each column ofeigen vector matrix with original data matrix. Finally a 3D sequence is reconstructed from principal component matrix.

3.Results and Discussion

In order to test the applicability of machine learning processing methods with frequency modulated thermal wave imaging (FMTWI), experiments have been carried on a CFRP specimen of thickness 4.3 mm, with a stacking sequence of 0/90 containing a set of flat-bottom holes of different diameters located at depths as shown in Figure 3.1.

FMTWI is employed with a linear frequency modulated incident heat flux of frequencies swept from 0.01 Hz to 0.1 Hz for duration of 100s. CFRP specimen is energized by two halogen lamps of 1 kW each. The thermal response of the sample during heating has been captured by a FLIR infrared imaging system at a frame rate of 20 Hz and the data has been processed using machine learning methods, pulse compression and phase methods.

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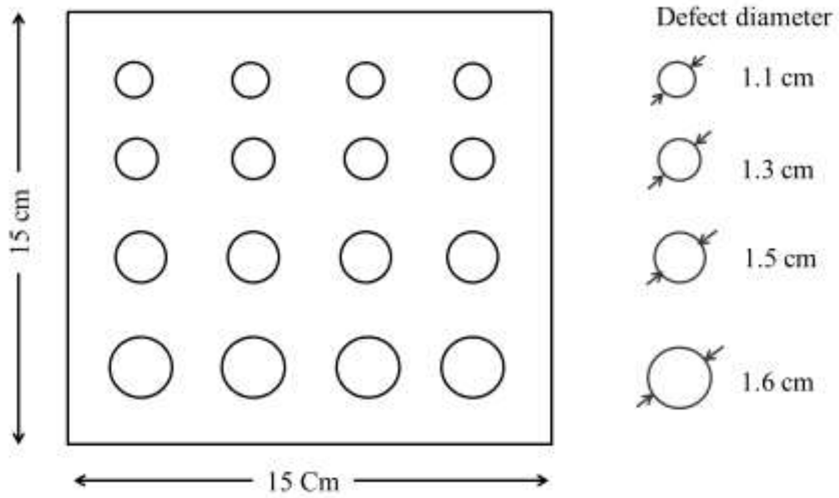

Figure 3.1. (Left) Layout of CFRP sample with flat-bottom holes of diameters a = 22 mm, b = 18 mm, c = 12 mm and d = 8 mm at depths of 1.6 mm, 1.74 mm, 1.7 mm and 1.65 mm, respectively, from the surface. (**Right).**Its cross-sectional view.

Thermal wave dispersion provides a variable phase delay for various frequency components contained in the chirp. In pulse compression, these delays are compensated and the energy of all these constituent signal components is concentrated at a delayed instant with the matched filter using cross-correlation. Subsurface discontinuities are differentiated by their existence in a few images in the correlation generated sequence, depending on their depth. A best correlation image, representing normalized correlation coefficients of all the pixels in the field of view at a delayed instant, has been used for detection. The correlation image of the above sample, as shown in Figure 3.7, represents all the incorporated defects. It is found that the shapes of all the defects are preserved.

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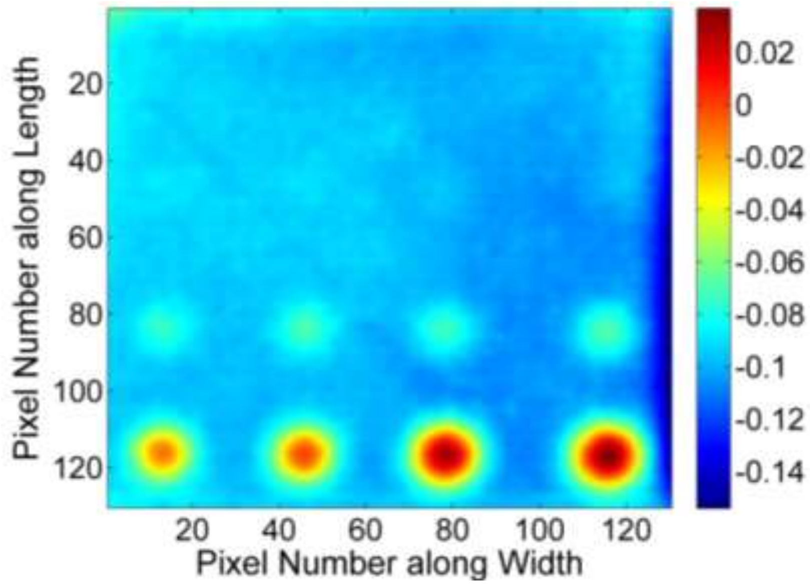

Figure 3.2 Correlation image of flat-bottom holes at a group delayed instant of 7.5 s.

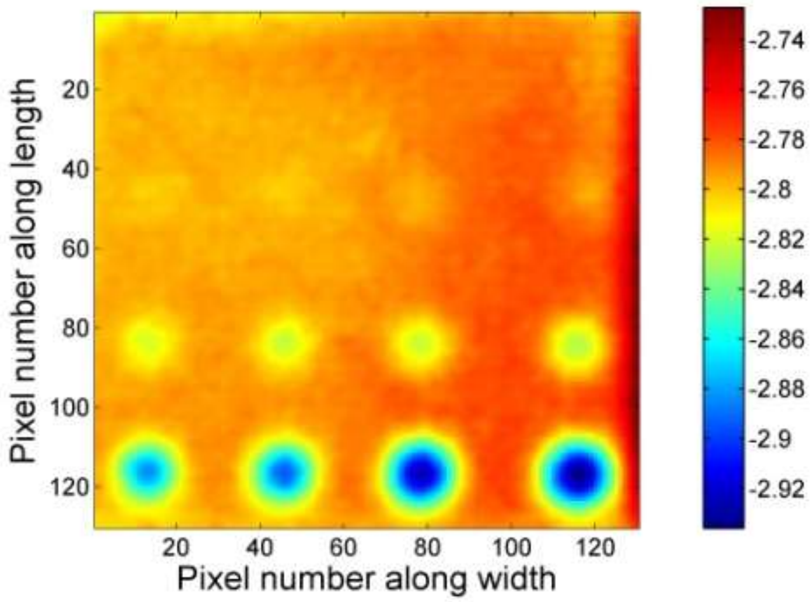

Figure 3.3 Phase image obtained at 0.02 Hz for flat-bottom holes.

In phase analysis, phase delay of the individual frequency components is analyzed for defect detection. The phase image generated at a frequency of 0.02 Hz is as shown in Figure 3.2. It is clear from Figures 3.7 and 3.8 that the correlation contrast over the defects is better than

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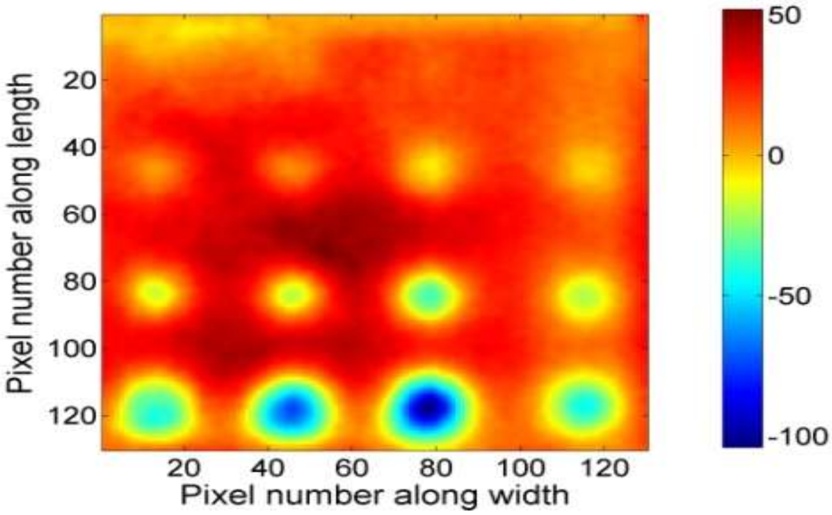

Figure3.4 Principal component Analysis

Detectability of the defects has been quantified in terms of signal to noise ratio of defects which is given by

$$\text{SNR (db)} = 10\log\left(\frac{\text{Mean of the defect region} - \text{mean of non defective region}}{\text{Standard deviation of non defective region}}\right)$$

Figure 3.12 exhibits a comparative defect detection capability of various data processing schemes applicable for FMTWI in terms of defect SNR. It is observed that Pulse compression and PCA are competing with each other among which, performing better than Pulse compression-based analysis. This is attributed because of its orthonormal projection capability for efficient feature separation which leads to better noise removal and enhanced thermal profile SNRs.

4. Conclusions

This work focuses on thermographic non-destructive evaluation using feature separation algorithms and also tried to highlight its edge over existing conventional methods for defect detection

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