

Comparative Analysis of Data Processing Methods for Non-Stationary Thermal Wave Imaging

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Abstract

Use of infrared waves for non-destructive sub surface analysis has been gaining interest due to its non-contact, whole field and surface radiation based detection supported by the application of various processing procedures and modulated excitation techniques. This paper introduces a novel Principal Component based analysis for subsurface anomaly detection using recently introduced digitized frequency modulated thermal wave imaging. Applicability of the proposed processing methodology has been verified through the experimentation carried over a mild steel specimen containing embedded flat bottom holes and compares it with existing phase analysis and conventional correlation techniques.

Keywords-- Infrared imaging, Phase analysis, Correlation, Principal Component Analysis.

I. INTRODUCTION

Recent years witnessed a tremendous growth in the use of various non-destructive testing (NDT) methods for assessing the integrity of the object without impairing its future usefulness. Infrared Thermography (IRT) is one of these testing methods in which the subsurface features of an object are identified using captured temperature map over object surface. This testing approach was further divided as passive and active. In the former approach inherent temperature map of an object is used to identify the subsurface anomalies [1]. Where as in the later, a modulated stimulus can be provided to the test object and its thermal response is captured using an infrared camera. Depending on the stimulus active thermography is further classified as Pulsed

Thermography (PT), Lock in Thermography (LT), Pulsed Phase Thermography (PPT) and Frequency Modulated Thermal Wave Imaging (FMTWI).

Pulsed thermography employs a short duration and high peak power stimulation to energize the surface of test object. This deposited energy initiates thermal waves at a very thin layer nearer to the surface which will propagate further into the interiors of the object due to thermal conduction. During its cooling phase, object surface is allowed back to equilibrium by dissipating energy to the surroundings and IR camera records the temporal thermal response. The localized temperature contrast at defect locations and their time of appearance etc., from this recorded thermal history is used for analysis in PT. In this method, high peak power sources remain as a drawback even though established image processing techniques helps to improve the capability of sub-surface defect detection.

Lock in thermography (LT) is a continuous wave imaging technique in which low power periodic wave stimulation (sine or cosine) is given to the test object unlike PT. Given stimulation further induces a similar mono frequency modulated thermal waves in the test object and subsequent thermal response is recorded with IR camera. The recorded thermal response is processed either using amplitude or phase based analysis. As merits of phase-based analysis being less sensitive to non-uniform radiation, non-uniform emissivity and providing more depth analysis favors its applicability. PPT Make use of frequency resolution capability of Fourier transform by employing phase based analysis over recorded thermal data acquired in experimentation similar to PT.

Frequency Modulated Thermal Wave Imaging (FMTWI) is introduced to overcome the problems of conventional methods like high peak powers of PT and repetitive experimentation with LT. In FMTWI, a heat stimulus of a suitable band of frequencies will be imposed on to the test object, which simultaneously probes the entire thickness in a single experimentation cycle unlike LT. Digitized frequency modulated thermal wave imaging (DFMTWI) is a digital counter part of the chirped version used in FMTWI.

II. METHODOLOGY

In the IRNDT, the test object is excited thermally using a modulated optical stimulus and the corresponding captured temperature map over the surface known as thermogram is extracted. The processing of this data is carried by considering the data from each pixel of the extracted thermograms and treating it as the thermal profile of corresponding pixel [2]. Consequently, the processing of the extracted data is carried by the processing unit. Initially the thermal response corresponding to the steady state term in stimulus is removed by using proper fitting methods. Furthermore, the processing techniques can be applied to these thermal profiles in order to eliminate the unwanted components like non-uniform radiation and thermal noise which are assumed to be embedded in the data. As a result of this procedure, the assessment of the defect's contrast enhances. So, the different processing methods like Phase Analysis, Correlation and Principle Component Analysis have been evolved and been explained below:

2.1 Phase Analysis

In this method, Fast Fourier Transform is applied on the thermal profiles corresponding to the data of the individual pixels and the phase corresponding to each and every frequency components is calculated. Using the phase values obtained, phasegrams are constructed where the phase corresponding to particular frequency component is visualized. By observing the phase contrast in these phasegrams defects at particular depth are obtained [3]. The corresponding frequency of samples in respective profiles obtained from Fast Fourier Transform is given by

$$f = F_s n / N$$

F_s = Sampling frequency or capture rate.

N = Total number of samples in thermal profile.

n = Number of the phasegram.

2.2 Correlation

In this method, from the captured thermograms the data corresponding to each pixel is arranged in form of a sequence called temporal thermal profile. Similarly, temporal thermal profiles of each and every pixel are generated and also a reference thermal profile is generated from the non defective region. The mean removed thermal profiles are then cross correlated with the reference signal and designated as normalized correlation data sequence. These normalized correlation data sequences corresponding to each and every pixel are generated at a delayed instant and are kept in their respective spatial locations to form correlation image. These images will provide a localized variation at defect region due to their dependency on delay and attenuation corresponding to the defect profiles [5].

2.3 PCA Method

PCA is one of the best known techniques in multivariate analysis. It could be defined as the orthogonal projection of the data on to lower dimensional linear space known as the principal subspace such that the variance of the projected data is maximized. The main scope of PCA is to reduce dimensionality to a lower extent. Basically, it is a linear projection technique for converting a matrix A of the dimension $m \times q$ to the matrix A_p of the lower dimension $s \times q$ ($s < m$) by projecting A onto a new set of principal axis. The best approach to the PCA is to use Singular Value Decomposition (SVD) of S : 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. Considering, the captured data is in three dimensional for performing principal component analysis, in order to set a convenient way for singular value decomposition, a subsequent pre-processing work need to be carried out. To be more precise, the original captured 3D data is transformed into a 2-Dimensional Matrix. It is processed in such a way that the time variations are ordered row wise, correspondingly the spatial variations along column wise. In order to make the PCA work accurately, a covariance matrix is

constructed for the above 2D matrix A by multiplying its Transpose and the mean removal matrix, in which the columns of U are the projection vectors that maximize the variance retained in the projected data Ap , subsequently U^T is the transpose of U . Then, the scatter matrix is flexible for performing singular value decomposition. After the application of SVD to the scatter matrix the resultant consists of three matrices which are Eigen vector matrix, diagonal matrix and transpose of Eigen vector matrix. The columns in Eigen vector matrix represent the time variations; subsequently the diagonal elements are the Eigen values and spatial variations as columns in third matrix. Next by multiplying each column of Eigen vector matrix with original data matrix, the principal components are determined. At last, a 3D sequence is reconstructed from principal component matrix.

III. EXPERIMENTAL DETAILS

3.1. Mild steel specimen

A mild steel specimen has been prepared for experimentation as in Fig. 1, the sample was 40cm long, 10cm wide and 1 cm thick and 10 artificial flat -bottomed holes were induced. The defect depth refers to distance between the top surfaces of the specimen to the top surface of the defect. The flat-bottom holes of 1cm and 0.5cm diameters at depths of 0.1cm, 0.15cm, 0.2cm, 0.25cm and 0.3cm were simulated respectively.

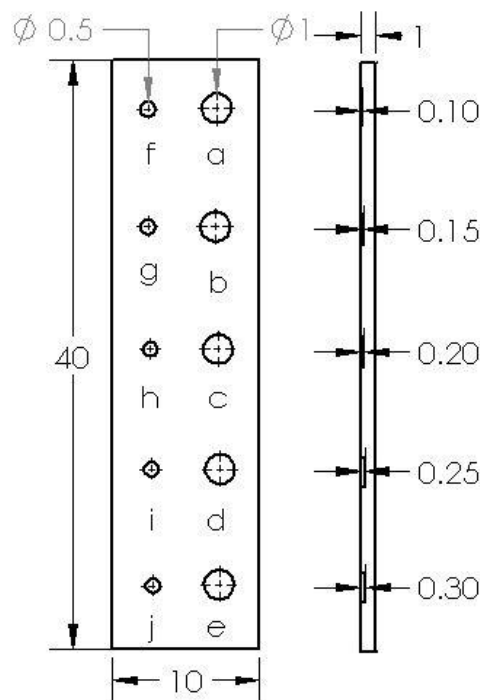


Fig. 1 Top and cross-sectional views of the experimental mild steel sample (all dimensions are in cm) with defects a, b, c, d, e of diameters 1 cm and f, g, h, i, j of diameters 0.5 cm, respectively.

3.2. Experimental setup

A schematic diagram of experimental setup is shown in Fig. 2. Two halogen lamps oriented onto the specimen were used to provide frequency modulated optical excitation driven through a control unit. The stimulus is absorbed by the object, corresponding thermal response is captured by infrared camera and sent to the processing unit.

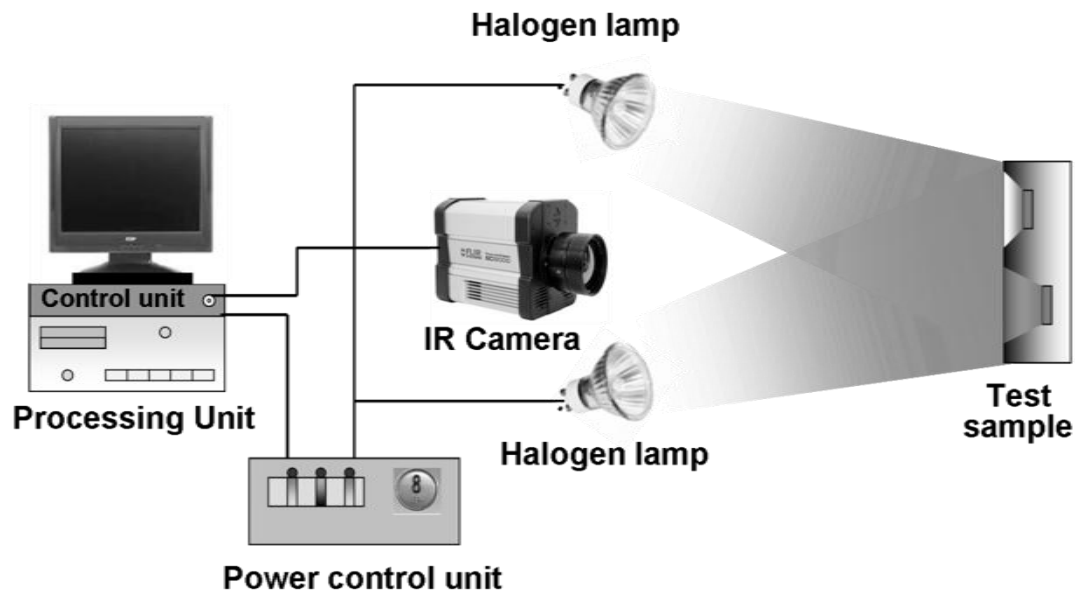
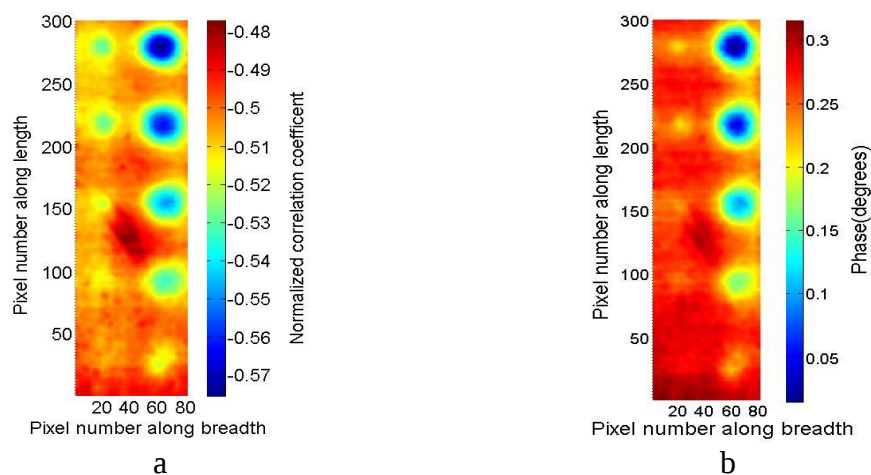


Fig. 2 A schematic of experimental setup

IV. RESULTS AND DISCUSSION

A mild steel specimen with the defects as show in Fig. 1was investigated using DFMTWI. The thermal response is captured using the infrared camera, then various processing techniques were applied on mean removed thermal profiles and the results were shown below.



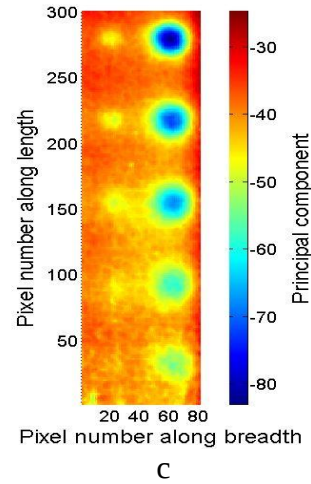


Fig. 3 Correlation image of DFMTWI (Fig. 3a), Phase image of DFMTWI (Fig. 3b), PCA image of DFMTWI (Fig. 3c)

From the above figures it is observed that the contrast for the deeper defects is more in the correlation image (Fig. 3a) but the shape of the deeper defects is not proper compared to the PCA image. In the phase image (Fig. 3b) the contrast for the shallow defects is better than deeper defects but the defects of smaller diameter are not having proper shape and also have low SNR values compared to that of correlation and PCA images. Unlike the correlation image the PCA image (Fig. 3c) preserves the shape for the shallow as well as deeper defects with minimum contrast for the deeper defects. In order to compare the best detection capability of various processing methods SNR values were quantitatively measured using formula [2]. Table. 1 illustrates the measured SNR values (in dB) of different defects in various schemes.

$$\text{SNR} = 20 \log \left(\frac{\text{mean of the defective area} - \text{mean of non defective area}}{\text{standard deviation of the non defective area}} \right) \text{dB}$$

Table. 1 SNR's of the defects

Defect	SNR for Correlation	SNR for Phase	SNR for PCA
a	46. 40	44. 58	43. 05
b	43. 78	41. 81	38. 72
c	39. 43	38. 13	37. 04
d	34. 13	29. 66	31. 78
e	23. 93	11. 07	27. 24
f	33. 88	15. 63	10. 93
g	31. 23	10. 40	15. 78
h	28. 46	12. 33	18. 01
i	23. 02	-5. 14	11. 51
j	13. 95	-16. 36	-4. 93

The SNR values in the above table depicts that PCA gives good SNR values for the deeper and smaller defects when compared to the phase image.

V. CONCLUSION

Detectability is presented for all the three processing methods phase, correlation and PCA for a mild steel specimen and their respective SNRs are also calculated. The results proved that the PCA method is applicable to thermal data and detecting of abnormalities is similar to correlation.

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