Investigations on probability of defect detection using differential filtering for pulse compression favourable frequency modulated thermal wave imaging for inspection of glass fibre reinforced polymers

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Abstract

Thermal Non-Destructive Testing and Evaluation (TNDT&E) plays a crucial role in industrial quality control and structural health monitoring of a variety of materials. Among various TNDT&E modalities, active Infrared Thermography (IRT) has emerged as an extremely promising approach and has gained enormous significance due to its quick, whole field, non-contact and quantitative defect detection capabilities. Pulse Compression favourable Thermal Wave Imaging (PCTWI) especially Frequency Modulated Thermal Wave Imaging (FMTWI) has become popular among a number of active IRT techniques because of increment in defect detection sensitivity as well as test resolution. The present work attempts to explore the applicability of differential filtering post processing scheme for pulse compression favourable FMTWI for enhanced detection contrast, resolution and Probability of Detection (PoD). The proposed scheme has been applied on a Glass Fibre Reinforced Polymer (GFRP) sample with sub-surface flat bottom hole (FBH) defects located inside the sample at different depths. The results presented clearly demonstrate that the differential contrast approach enhances the defect detection probabilities by considering maximum and minimum deviation dip values as a figure of merit. Hence, pulse compression favourable FMTWI employing differential filtering manifests higher Probability of Detection (PoD) for defects located at different depths as compared to taking into account the peak Correlation Coefficient (CC) as a statistical figure of merit. Further Probability of Detection (PoD) of the pulse compression favourable FMTWI technique has been improved by differential filtering post-processing based scheme that reduces the memory requirement, computational cost as well as complexity.

1. Introduction

Infrared Thermography (IRT) is a non-contact, non-invasive, two-dimensional and reliable approach that has attained enormous importance in TNDT&E community. Active IRT involves the application of an external thermal energy over the test object followed by capturing and monitoring the thermal response over the test object. Owing to the propagation of thermal energy that is impeded by thermal inhomogeneity, temporal variations in temperature on the surface at the location over the defects is observed. This thermal contrast obtained at each defect location due to thermal inhomogeneity is captured and post-processed for sub-surface defect characterization in IRT. IRT is realized either by a passive or by an active approach. Active IRT techniques are widely classified into pulse based and modulated thermography, depending upon the shape of external thermal stimulus applied [1]. Pulse based active IRT techniques are further grouped as
Pulse Thermography (PT) and Pulse Phase Thermography (PPT) depending upon the post processing method adopted [2]. On the other hand, modulated thermography methods are further categorised as Lock-in Thermography (LT), Frequency Modulated Thermal Wave Imaging (FMTWI), Digitized Frequency Modulated Thermal Wave Imaging (DFMTWI) and Barker Coded Thermal Wave Imaging (BCTWI). Among these large number of active IRT techniques, PPT and LT gained wide popularity due to their low complexity and fast implementation time. However, these techniques hold certain limitations such as high peak power requirement (Pulse based thermographic methods) and limited resolution in case of monofrequency excited LT. In order to address and overcome these limitations, FMTWI is introduced as it probes desired band of thermal frequencies with moderate peak power requirement in a limited span of time. The technique of FMTWI involves modulating the incident heat flux in a reasonable time span, with an appropriate frequency sweep depending upon the thermo-physical properties as well as the thickness of the specimen under test. Furthermore, pulse compression favourable post processing schemes enhance the defect detection sensitivity and depth resolution of FMTWI [2]. This paper focuses on the enhanced quantitative analysis of pulse compression favourable FMTWI via Probability of Detection (PoD) curves; along with the application of differential filtering based post processing measure; in order to achieve better visualization for the subsurface defects.

PoD builds a statistical framework in order to perform inspection reliability of a pulse compression favourable FMTWI for a GFRP test sample with FBH as sub-surface defects [3]. In this study, GFRP specimen with thirteen FBH defects are inspected using Pulse compression favourable FMTWI. The Cross Correlation (CC) profiles obtained at each defect depth after pulse compression are utilized for the overall computation of PoD. The maximum and minimum deviation dips obtained after the differential filtering of pulse compressed correlation profile data \( \frac{d(CC)}{dt} \), are therefore, considered as a statistical figure of merit. Present work provides an insight on the applicability of Pulse compression favourable FMTWI for testing and evaluation of GFRP specimen by considering the differential filtering as a post processing algorithm. The estimation of detection probabilities are calculated considering maximum and minimum deviation dips obtained as a result of differential filtering \( \frac{d(CC)}{dt} \), as continuous signal responses that are plotted as a function of aspect ratio (diameter / depth) of the GFRP specimen under test.

2. Sample and experimentation details

In order to perform the quantitative analysis for evaluating the sub-surface defect detection abilities of the proposed pulse compression favourable FMTWI, a GFRP test sample with FBHs has been considered, as shown in figure 1(a)(i). The values of aspect ratio with increasing depths are: 1.846, 2, 2.181, 2.4, 2.666, 3, 3.428, 4, 4.8, 6, 8, 12 and 24. Experiments have been performed with two halogen lamps of each 1 kW power, placed at a distance of one metre from GFRP test specimen, having 13 FBH of diameter of 6 mm, at respective depths of 0.25 mm—3.25 mm at an interval of 0.25 mm, as shown in figure 1(a). This GFRP specimen is excited by an imposed frequency modulated incident heat flux, using two halogen lamps of each 1kW power; for a duration of 100 s; as shown in figure 1(b). A cooled infrared camera with a mid-infrared spectral region (2.5 \( \mu m \) to 5.1 \( \mu m \) transmission window) is used in experimentation with a spatial resolution of 320 \( \times \) 240.

Infrared image sequence during the active heating is captured at a frame rate of 25 frames/seconds with an infrared camera (InSb focal plane array with a sensitivity of 20 mK) placed at about one metre away from the test sample as shown in figure 1(b). The field of view of the camera at one metre standoff distance from the test sample is about 1 square foot. The typical temperature rise is obtained for a frequency modulated incident heat flux at a depth of 3.25 mm over the GFRP test specimen as is shown in figure 2(a). The mean rise in temperature distribution during the active heating is removed by fitting the temperature distribution over a depth of 3.25 mm with a first order polynomial (linear fit) to obtain the zero mean temperature distribution as shown in figure 2(b).

Further, matched filtering based post processing has been carried out on the captured mean removed temperature distribution sequence obtained over a depth of 3.25 mm (as shown in figure 2(b)) in order to reconstruct the pulse compressed profile with peak CC. The reconstructed pulse compression profiles are generated by cross correlating the zero mean temperature distribution captured over a particular defect depth with the zero mean temperature distribution at the sound/background region. The reconstructed pulse compressed sequences obtained from mean removed temperature profiles for all depths ranging from 0.25 mm to 3.25 mm for a GFRP test specimen with pulse compression favourable FMTWI is demonstrated in figure 3.

The reconstructed pulse compressed thermal sequence is further processed as follows. First, the total compressed pulse data obtained for each defect depth has been considered to calculate peak CC values. In the latter part, only half of main lobe data from pulse compressed profiles has been considered for differential
filtering post-processing scheme in order to obtain maximum and minimum deviation dip values. For the purpose of PoD estimation, both peak CC from pulse compressed correlation profiles as well as maximum and minimum deviation dip values from differentiated half-main lobe \([d(CC)/dt]\) are considered for estimation of PoD.

Figure 1. (a) (i) Geometrical layout of GFRP sample having flat bottom hole (FBH) sub-surface defects (all dimensions are in mm) (ii) front view of the sample (iii) infrared view of the front view of the GFRP sample. (b) Experimental arrangement used for frequency modulated thermal wave imaging (FMTWI).
3. Mathematical formulations

A defect of aspect ratio ‘a’ over the experimental GFRP test specimen creates a quantitative signal response set ‘â’ (peak CC as well as maximum and minimum dip values) which are obtained by taking the differentiation of half main lobe $d(CC)/dt$ during the post processing of reconstructed pulse compressed correlation profiles. The statistical distribution of the continuous response signal set ‘â’ with respect to any defect dimension (aspect ratio) in this case yields a PoD curve [1]. Following steps reveal the detailed explanation of obtaining a PoD curve from ‘â’ versus ‘a’ source data set, where ‘â’ represents the maximum CC value in the first case and maximum and minimum deviation dip values in the second case after taking differential filtering into consideration for the reconstructed pulse compressed profiles at each depth over the experimental GFRP specimen.

For the statistical analysis, it has been a common practice to assume that there exists a linear relationship between $\ln(â)$ and $\ln(a)$; and the distribution for signal deviation errors is assumed normally distributed about that linearly regressed line. Therefore, this paper highlights the calculation of PoD curves by keeping the distribution of quantitative response data set ‘â’ with a cumulative lognormal fit. The ‘â’ (peak CCs as well as maximum and minimum deviation dips after differential filtering) versus aspect ratio ‘a’ is analysed to choose the best model that is linearly regressed, so a straight line properly describes it and the variance remains approximately constant.

The log-log linear regression model is expressed as:

$$\ln(â) = \beta_0 + \beta_1 \ln(a) + \Omega$$

where, $\beta_0$ is the intercept and $\beta_1$ is the slope, and $\Omega$ is the standard error assumed to have normal distribution with zero mean and constant standard deviation $\sigma_\Omega$.

In general, if $f_\gamma(â)$ denotes the probability density for â values for a pre-defined depth of aspect ratio ‘a’, PoD (a) is generalised as:
\[
PoD(a) = \int_{\hat{\alpha}_{dec}}^{\infty} f_\alpha(\hat{\alpha}) \, d\hat{\alpha}
\]

where, \( \hat{\alpha}_{dec} \) represents the decision threshold determined on the basis of noise analysis. For the case of temporal data, \( \hat{\alpha}_{dec} \) is determined by observing the quantitative response data sets (reconstructed correlation profiles). Generally, the value of \( \hat{\alpha}_{dec} \) is kept close to the mean values that are obtained for \( \hat{\alpha} \).

Since, equation (1) provides the \( \ln(\hat{\alpha}) \) versus \( \ln(a) \) relationship, therefore, modelling of PoD(a) function via log-linear regression is expressed as:

\[
PoD(a) = 1 - \mathcal{O}\left\{ \frac{\ln(\hat{\alpha}_{dec}) - \beta_o + \beta_1 \ln(a)}{\sigma_\Omega} \right\}
\]

where, \( \mathcal{O}(\cdot) \) indicates the standard normal distribution. Therefore, exploiting the symmetry properties, equation (3) is reduced to:

\[
PoD(a) = 1 - \mathcal{O}\left\{ \frac{\ln(a) - \frac{\ln(\hat{\alpha}_{dec}) - \beta_o}{\beta_1}}{\sigma_{\Omega/\beta_1}} \right\}
\]

The parameters \( \beta_o, \beta_1 \) and \( \sigma_\Omega \) can be best estimated from the experimental reconstructed thermal response data (in the form of CC values) using Generalised Linear Models or Linear Regression Models \[5\]. The maximum CC values corresponding to maximum deviation dip values are of the values: 0.2348, 0.2550, 0.2777, 0.3040, 0.3341, 0.3692, 0.4095, 0.4589, 0.5171, 0.5877, 0.6745, 0.7815 and 0.9087. The CCs corresponding to peak correlation from pulse compressed profiles are: 0.1279, 0.1371, 0.1475, 0.1599, 0.1740, 0.1908, 0.2106, 0.2358, 0.2670, 0.3080, 0.3644, 0.4490 and 0.5968.

The maximum CC values corresponding to minimum deviation dip values: 0.3749, 0.3855, 0.3970, 0.4129, 0.4239, 0.4400, 0.4578, 0.4791, 0.5040, 0.5347, 0.5740, 0.6279 and 0.7141.

Equation (4) denotes the cumulative lognormal distribution function, with means and standard deviation of log (aspect ratio) is given by:

\[
\mu_s = \frac{\ln(\hat{\alpha}_{dec}) - \beta_o}{\beta_1}
\]

and, \( \sigma_s = \frac{\sigma_\Omega}{\beta_1} \)

The statistical values for the determination of mean \( \mu_s \) and the standard deviation \( \sigma_s \) are random, generated for the peak cross correlation CC values corresponding to each depth of GFRP sample. The following section provides the complete methodology for estimating the statistical parameters related to the calculation of PoD(a) function by first approximating the regression coefficients \( \beta_o \) and \( \beta_1 \) and thereby calculating the statistical values of \( \mu_s \) and \( \sigma_s \).

Generalized Linear Models or Least Square Regression (GLM/LSR) method means fitting a cloud of ‘N’ data points \((x_i, y_i)\), in a straight line of the form:

\[
y = mx + \omega
\]

where, ‘i’ increments from 1 to N. Here, \( y_i \) represents the peak CC values whereas \( x_i \) represents the aspect ratios for a given GFRP specimen.

We generalize a straight line of the form:

\[
f(x) = mx + n
\]

Our main goal is to therefore determine the values for the constants \( m \) and \( n \), that are chosen as the best estimates for unknown parameters \( \hat{\alpha} \) and \( \hat{\omega} \). We can define the term \( \epsilon \) as the weighted sum of the residual errors, that arise due to the minor deviations between the random signal points and the fitted line.

\[
\epsilon(m, n) = \sum_{i=1}^{N} w_i r_i^2 = \sum_{i=1}^{N} w_i [f(x_i) - y_i]^2
\]

\[
= \sum_{i=1}^{N} w_i (mx_i + n - y_i)^2
\]

The ‘N’ residuals for ‘N’ data points can be given by:

\[
r_i = [f(x_i) - y_i]
\]

Here, \( w_i \) represents the weight given to each \( i \)th data point in (8).
The 'Least Squares' i.e. the squares of the residuals should be the least, for that \(\epsilon (m, n)\) should be minimum in order to best estimate the parameters \(m\) and \(n\). In order to minimize \(\epsilon\), we are differentiating the function \(\epsilon(m, n)\) w.r.t the unknown parameters to be estimated \(m\) and \(n\), and setting each of the derivatives to zero.

Therefore,

\[
\frac{\partial \epsilon}{\partial m} = 0 \quad \text{and} \quad \frac{\partial \epsilon}{\partial n} = 0
\]  

(9)

After the calculation of the derivatives, we have:

\[
Z_1 m + Z_1 n = P \quad \text{and} \quad Z_0 m + W n = Q
\]  

(10)

On solving, the resultant of sums will be like:

\[
Z_2 = \sum x_i^2 w_i, \quad Z_1 = \sum w_i x_i, \quad P = \sum w_i x_i y_i
\]

and \(W = \sum w_i\) and \(Q = \sum w_i y_i\); for all sums calculated from \(i = 1\) to \(N\).

Equation (10) can be solved further to get the parameters \(m\) and \(n\) as follows:

\[
m = \frac{1}{\Delta (W, P - Z_1, Q)} \quad \text{and} \quad n = \frac{1}{\Delta (Z_2, Q - Z_0, P)}
\]  

(11)

Here, \(\Delta\) in (11) provides the determinants for the coefficients given by:

\[
\Delta = W Z_2 - Z_1^2.
\]

In order to estimate the values of statistical parameters that will best describe the experimental data, the log likelihood function is maximised, yielding the maximum likelihood estimate. The modified quantitative data set is statistically processed and Probability of Detection (PoD) curves are plotted primarily using equations (3)–(5).

The probabilities of detection that are generated considering the maximum deviation dip values of differential filtering (represented by red colour line in figure 5(a)) are estimated as: 0.2348, 0.2550, 0.2777, 0.3040, 0.3341, 0.3692, 0.4095, 0.4589, 0.5171, 0.5877, 0.6745, 0.7815 and 0.9087 for aspect ratio of all depths, ranging from shallower to deeper defects respectively.

The probabilities of detection that are generated considering the minimum deviation dip values of differential filtering, (represented by green colour line in figure 5(b)) are estimated as: 0.3749, 0.3855, 0.3970, 0.4129, 0.4239, 0.4400, 0.4578, 0.4791, 0.5040, 0.5347, 0.5740, 0.6279 and 0.7141; for all aspect ratio of all depths, ranging from shallower to deeper defects respectively. The probabilities of detection that are generated considering the peak CC of pulse compressed temporal profiles (represented by blue colour line in figures 5(a) and (b)) are estimated as: 0.1279, 0.1371, 0.1475, 0.1599, 0.1740, 0.1908, 0.2106, 0.233 58, 0.2670, 0.3080, 0.3644, 0.4490 and 0.5968; for all aspect ratio of all depths, ranging from shallower to deeper defects respectively.

4. Results and discussion

The reconstructed pulse compressed profiles procured at each defect depth as shown in figure 3 are analysed for the quantitative assessment of Pulse compression favourable FMTWI technique. The peak Correlation Coefficients (CC) are considered as illustrated in figure 3 for all 13 defects over the experimental test specimen and are therefore, linearly regressed with aspect ratio ‘a’ in order to calculate the PoD curves.

With the process of differential filtering, \(d(CC)/dt\) profile data will ensure data compression along with the pulse compression post processing scheme as the entire energy of the main lobe gets concentrated, leading to enhanced differential contrast and therefore, higher probability of defect detection. The differential filtering ensures that all the edges are preserved, leading to better depth resolution and detection ability, making pulse compression favourable FMTWI more robust technique as compared to its counterparts.

The maximum and minimum deviation dip values are obtained as a result of differential filtering. Differential filtering is a post-processing scheme that involves the differentiation of half of main lobe of Cross Correlation (CC) profiles obtained at each defect depth of experimental test specimen, denoted by \([d(CC)/dt]\). The maximum and minimum deviation dips obtained for a particular spatial location of 3.25 mm; that are considered as a statistical dimension to evaluate the inspection reliability is as shown in figure 4(a). The reconstructed differentiated profiles generated from the pulse compressed profiles obtained for all defect depths over the test sample is as shown in figure 4(b).

It has been observed that the probability of defect detection is more superior when the maximum and minimum deviation dip values are considered as a figure of merit. These differentiated values are obtained after
the differentiation of half of main lobe of pulse compressed correlation profiles and are compared with the peak CC values generated from the reconstructed pulse compressed profiles at each defect depth as shown in figures 5(a) and (b) respectively.

5. Conclusion

Results highlight the merits of differential filtering based post processing technique for pulse compression favourable FMTWI in terms of enhanced contrast for visualization of sub surface defects. The quantitative inspection capabilities of this proposed approach is highlighted by estimating the PoD curves, by considering maximum and minimum deviation dip values and aspect ratio (size-to-depth ratio) as figure of merit. The maximum and minimum deviation dip values are procured by differentiating the half of main lobe of pulse compressed correlation profiles \(\left[\frac{d(CC)}{dt}\right]\), of the temporal temperature distribution obtained at each spatial location over the experimental GFRP specimen. It is concluded from the experimental results that the higher PoD is achieved when the differentiated values of half- main lobe of reconstructed cross correlation profiles are compared to the peak CC as a statistical parameter for defects of all aspect ratios. Further the pulse compression favourable FMTWI, along with the proposed differential filtering approach makes this scheme as a data reduction and memory efficient method.

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Data availability statement

No new data were created or analysed in this study.

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