An Industrial Vision System For Sub Surface Visualization Of Structural Steel Sample Using Digitized Frequency Modulated Thermal Wave Imaging: A Numerical Study

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Abstract. Non-stationary thermal wave imaging techniques have proved to be an indispensable approach for non-destructive testing and evaluation of solids. This work emphasizes on digitized frequency modulated thermal wave imaging for characterization of steel specimen having inclusions. Multi-transform techniques have been implemented onto the captured thermal response to visualize the sub-surface inclusions and further compared by taking signal to noise ratio into consideration.

Keywords: Finite element analysis, Hilbert Transform, Non-stationary thermal wave imaging, Signal to noise ratio (SNR).

Introduction

Non-destructive testing and evaluation (NDT&E) of material using infrared thermography (IRT) enables quick and reliable analysis, without impairing its physical, chemical or mechanical properties. Industrial IRT can be broadly classified into two approaches, namely passive and active [1-5]. In passive approach the test specimen and its sub-surface inclusions naturally exhibit different thermal contrast at ambient temperature whereas in case of active approach, an external stimulus is necessary to induce significant thermal contrast. Depending on the external stimulus, different approaches of active thermography have been developed, such as pulse thermography (PT) [1], lock-in thermography (LT) [3], pulse phase thermography (PPT) [4]. The active approach finds numerous applications in thermal NDT (TNDT). Active IRT is widely used to retrieve the information regarding thermo-physical properties or NDT&E of materials. Recently introduced non stationary thermal wave imaging methods [5-11] mainly, frequency modulated thermal wave imaging (FMTWI) and its digitized version (DFMTWI) [6,7] plays a vital role in testing and evaluation by overcoming the problems associated with the conventional methods (PT, LT and PPT) such as high peak power requirements of pulse based techniques and long experimentation time of modulated LT [11].

In FMTWI the incident heat flux is varied by driving the heat sources with a linear frequency modulated signal (in up chirp form), which causes a similar frequency modulated surface heating over the sample. This helps to introduce desired band of frequencies with
significant magnitude into the test sample which improves the test resolution. In contrast to FMTWI, modulation of the heat sources is much easier in DFMTWI. Furthermore, in DFMTWI we can probe more energy into the sample by introducing harmonics along with the desired band of frequencies which may improve the depth resolution for near surface defects. This paper highlights the capability of DFMTWI technique in visualizing inclusions present in modeled structural steel sample. Further, Multi-transform techniques have been implemented and compared by taking signal to noise ratio (SNR) into consideration [11].

Modeling, Simulation & Data Analysis

In this work a 3D finite element analysis (FEA) has been carried out on a steel sample using COMSOL Multiphysics. The mild steel sample with four inclusions {Calcium Oxide (CaO), Magnesium Oxide (MgO), Aluminium Oxide (Al$_2$O$_3$) and Air} (shown in Fig. 1) has been modeled with a finer mesh using 3D tetrahedral elements.

![Fig. 1. Layout of the modeled mild steel sample with inclusions. (a).Calcium Oxide (CaO), (b). Magnesium Oxide (MgO), (c). Aluminium Oxide (Al$_2$O$_3$) and (d). Air](image)

The FEA was carried out by imposing a DFM heat flux over the surface of the test object and the surface thermal response has been captured at a frequency of 25 Hz. The simulations were carried out under adiabatic boundary conditions, with the sample at an ambient temperature of 300 K. The sample properties and the introduced inclusions are as given in Table 1.

<table>
<thead>
<tr>
<th>Material</th>
<th>CaO</th>
<th>MgO</th>
<th>Al$_2$O$_3$</th>
<th>Air</th>
<th>Mild steel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density (Kg/m$^3$)</td>
<td>3350</td>
<td>3580</td>
<td>3975</td>
<td>1.225</td>
<td>7850</td>
</tr>
<tr>
<td>Thermal Conductivity (W/m-K)</td>
<td>15</td>
<td>36</td>
<td>30.3</td>
<td>0.024</td>
<td>60.5</td>
</tr>
<tr>
<td>Specific Heat (J/Kg-K)</td>
<td>749</td>
<td>960</td>
<td>880</td>
<td>1010</td>
<td>434</td>
</tr>
</tbody>
</table>

The simulated data has been further processed for the detection of inclusions. This is carried out by constructing the phase images obtained from the time domain matched filter approach and the conventional frequency domain analysis as follows:

Time Domain Matched Filter Approach. In time domain analysis, time domain phase image is constructed from the circular convolution of the in-phase as well as quadrature-phase of the chosen reference signal with that of the captured temporal thermal response. It is given as [10,12]:

\[ \text{Signal} = \text{Reference} \ast \text{Response} \]
where $sgn(f)$ is the signum function and $Ref(f)$ and $P(f)$ are the Fourier transforms of the reference thermal signal $ref(t)$ and the captured thermal response $p(t)$. $IFFT$ and $*$ denote the inverse Fourier transform and complex conjugate operators, respectively. The quadrature of the reference temperature response is obtained using Hilbert Transform (HT) and the frequency response is obtained through Discrete Fourier Transform (DFT).

However, the time domain correlation coefficient (CC) image is obtained from the circular convolution between the chosen reference signal and the captured temporal thermal response given as follows [10,12]:

$$CC(t) = IFFT\{Ref(f)^* \cdot P(f)\}$$

The procedure is schematically represented in Fig.2.

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**Figure 2.** The processing approach adopted for construction of pulse compressed correlation co-efficient and phase contrast images [10,12].

**Frequency Domain Analysis.** The frequency domain phase image is computed as follows:

Suppose $p(n)$ is a temporal temperature data captured at a predefined rate obtained for a given pixel $(i,j)$ in the field of view, then its Fourier transform $P(f)$ is given as [4-6]:

$$P(f) = \frac{1}{N} \sum_{n=0}^{N-1} p(n) \exp \left( -j \frac{2\pi fn}{N} \right) = Real(f) + Imag(f)$$

where $Real(f)$ and $Imag(f)$ are the real and imaginary components of $P(f)$ respectively. Further, the phase can be computed as follows [4-6]:

$$\phi(f) = \tan^{-1} \left( \frac{Imag(f)}{Real(f)} \right)$$

**Results and Discussion**

The present works highlights the capability of DFMTWI approach in visualizing the inclusions present in a structural mild steel sample. In this approach, the test specimen is allowed to undergo a known controlled digital modulated thermal stimulation sweeping their
fundamental frequency range from 0.01 Hz to 0.1 Hz in 100 s, and the corresponding thermal response of the surface is captured. The temporal mean raise in captured thermal response is removed using a first-order data fitting. Post processing multi-transform (frequency and time domain) techniques have been implemented onto zero mean thermal response and the results obtained are shown in Fig. 3. The conventional frequency domain image is shown in Fig. 3. (a), whereas the time domain phase image is shown in Fig. 3. (b). The time domain correlation coefficient image is shown in Fig. 3. (c). Results obtained clearly shows that materials with different thermal properties gives different thermal contrasts, therefore can be easily utilized for identification of sub-surface feature characteristic and its properties.

Fig. 3. Results obtained for DFMTWI technique for frequency and time domain transform techniques (a). frequency domain phase image. (b). time domain phase image. (c). time domain correlation coefficient image.

Further, Thermal contrasts have been quantified in terms of the materials SNR as computed using:

$$SNR = 20 \log \left( \frac{Mean \ of \ the \ defective \ area - Mean \ of \ the \ non \ defective \ area}{Standard \ deviation \ of \ non \ defective \ region} \right)$$  \hspace{1cm} (5)

SNRs have been computed for different inclusions in the mild steel sample for images obtained with different analysis methods as presented in Table 2.
Table 2. Signal to Noise Ratio

<table>
<thead>
<tr>
<th>TRANSFORM TECHNIQUE</th>
<th>SNR in Decibels (dB) for different inclusions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CaO (a)</td>
</tr>
<tr>
<td>FFT Phase</td>
<td>60.2195</td>
</tr>
<tr>
<td>Time Domain Correlation</td>
<td>76.6976</td>
</tr>
<tr>
<td>Time Domain Phase</td>
<td>76.0767</td>
</tr>
</tbody>
</table>

Conclusion

The proposed work highlights the capability of DFMTWI technique to visualize different inclusions present in the test object. Various multi transform techniques have been introduced in time and frequency domain and comparisons have been made among them by taking SNR into consideration. Results clearly show that the time domain approaches are far superior to that of frequency domain approaches.

References


