INTRODUCTION

Thermography or infra-red (IR) imaging is an increasingly popular non-contact nondestructive evaluation (NDE) technique used for material damage inspection. Active thermography focuses on the detection of sub-surface flaws like cracks, material losses and foreign particle inclusions. Here the material under test is subjected to intentional external heating so that the hidden defects reveal themselves by causing surface hot spots under thermal non-equilibrium condition. The success of active thermography techniques eventually depends on the quality of the raw thermograms. Good thermograms are obtained when the test material is a perfect black body. Hence for laboratory testing, the bodies are blackened, although the blackening is rarely perfect. Thus large scale surface emissivity variation poses a major challenge to the thermography community which leads to the requirement of an image processing algorithm which can handle large-scale surface emissivity variation under improperly blackened (or perhaps un-blackened) condition. An image reconstruction algorithm by the authors, to remove such surface artifacts in lock-in thermography (LT) [1], has just been published [2], and its salient features, implementation and application is summarized here.

ALGORITHM

The proposed algorithm attempts to enhance transient LT images, and has the following three major aims.

1. Reduction in the duration of traditional LT by polynomial fit trend removal approach that allows working in the transient regime (rather than steady-state), at a given frequency.
2. Removal of surface artifacts in IR images due to non-homogeneous surface emissivity, by mathematical reconstruction of time-domain surface temperature video.
3. Correction of background gradient in IR images due to non-uniformity of the heating system by 3D polynomial fit.

Figure 1 shows the steps of the proposed algorithm. Step 1 facilitates the use of transient lock-in thermography data to calculate the phase and amplitude images. This is achieved by fitting and subtracting polynomials from recorded video. Step 2 evaluates the phase and amplitude images by Fourier transformation [1] of the trend removed video obtained in step 1. Once the phase and amplitude images are calculated, the time domain sinusoidal lock-in video can be mathematically reconstructed as shown in step 3. This video is free from time domain temperature noise. In this reconstructed video, there exist frames where the surface artifacts due to non-homogeneous emissivity disappear completely. These frames happen to be those where the sinusoidal heating excitation exhibits zero crossings. Naturally in one heating cycle, there would be two such frames. In positive going zero-crossing, the defects are visible as cold spots, while in negative going zero-crossing, hot spots are observed. Once the optimum frame
Fig. 1: Steps of the proposed image reconstruction algorithm (adapted from [2])

(a) Step 1: Pixel wise polynomial fit is performed over temperature vs. time data.

\[
\begin{align*}
I_{\text{sin}}(x, y) &= \int_0^T T_{\text{sin}}(x, y, t) \sin \omega t \, dt \\
I_{\text{cos}}(x, y) &= \int_0^T T_{\text{cos}}(x, y, t) \cos \omega t \, dt \\
\phi(x, y) &= \tan^{-1}\left(\frac{I_{\text{cos}}(x, y)}{I_{\text{sin}}(x, y)}\right) \\
A(x, y) &= \sqrt{I_{\text{sin}}(x, y)^2 + I_{\text{cos}}(x, y)^2}
\end{align*}
\]

(b) Output of step 1: Trend subtracted surface temperature vs. time, with inset showing one cycle.

(c) Step 2: The phase and amplitude information of the flattened signal in Fig. 1b extracted by Fourier transform.

\[
T_{\text{ref}}(x, y, t) = A(x, y) \sin \left\{ \omega t + \phi(x, y) \right\}
\]

(d) Output of step 2: Phase and amplitude images.

(e) Step 3: Pixel wise sinusoidal signals reconstructed using the information, extracted in step 2.

\[
\omega t_0 + \phi_x = \pi \\
t_0 = \frac{(\pi - \phi_x)}{\omega} \\
t_0: \text{time of zero crossing} \\
\phi_x: \text{phase of the directly reflected signal} \\
\omega: \text{angular frequency of excitation}
\]

(f) Output of step 3: Reconstructed video, free from noise.

(g) Step 4: Identification of the zero crossing frame, indicated by the vertical line in Fig. 1f.

A polynomial, of the form

\[
z = \sum_{i=0}^{n} \sum_{j=0}^{n} a_{ij} x^i y^j
\]

is fitted over the thermogram obtained in step 4.

(h) Step 5: A 3-dimensional surface fit to subtract heating non-uniformity.

(i) Final processed image

An optimal frame where the surface artifacts are absent. The effect of non-homogeneous heating is corrected as well.
Fig. 2: Dimensions of the mild steel sample (in mm) [2]

Fig. 3: Reconstruction of mild steel thermogram (adapted from [2])

APPLICATION

The complete algorithm was applied on a piece of mild steel sample blackened with viscous carbon paint (poster colour). The sample drawing with blind hole defects is shown in Fig. 2. The blackening was improper and some metallic surface patches were left. Under LT at 50 mHz, these surface patches appear more prominently in the amplitude and phase images suppressing the actual defects (Fig. 3a and Fig. 3b). Further the brush strokes from the blackening process are also visible in these images as strip noise. To obtain the enhanced images of the defects, the following steps were performed.

1. Transient LI thermography was performed at 50 mHz with a reflector placed in the field of view of the camera.
2. The time domain temperature trend due to DC heating was removed by pixel wise polynomial fits.
CONCLUSION

The proposed algorithm overcomes the limitations of LT phase and amplitude images. It reduces the duration of LI thermography by allowing transient regime testing. The algorithm also enables correction of heating non-uniformity by surface fitting. The implementation of the algorithm is done in C++. It takes less than 2 minutes for the entire process to complete on a 320 × 240 pixel, 400 frame video.

REFERENCES