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Stable principal component pursuit-based thermographic data analysis for defect detection in polymer composites

Zhengbing Yan [a], Chun-Yu Chen [b], Linkai Luo [b], Yuan Yao [b,*]

[a] College of Physics and Electronic Information Engineering, Wenzhou University, Wenzhou 325035, China
[b] Department of Chemical Engineering, National Tsing Hua University, Hsinchu 30013, Taiwan

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ABSTRACT

Defects such as inclusions and voids are commonly observed in fiber reinforced polymer (FRP) composites. In order to ensure the quality of FRP products, it is desirable to have reliable and non-destructive testing techniques for detecting defects. Among existing techniques, pulsed thermography (PT) has the advantages of a wide scanning range and simple operation. However, thermal images generated using PT are often noisy, and can contain non-uniform backgrounds resulting from uneven heating. As a result, post-processing is necessary to improve the detection capability of PT. In this study, stable principal component pursuit (SPCP) is integrated with a moving-window strategy to decompose thermographic data into three parts: a low-rank matrix to approximately extract background information, a dense noise term containing most of the measurement noise, and a sparse matrix reflecting the defects in the tested specimen. In this manner, improved detection results can be obtained from the reconstructed thermal images based on the sparse matrix. The effectiveness of the proposed method is illustrated through experiments.

1. Introduction

Fiber reinforced polymer (FRP) composites are constructed from a polymer matrix that is reinforced with fibers, such as glass or carbon, which usually have high mechanical strength, low density, and high chemical stability. Owing to these desirable properties, FRPs are commonly employed in the aerospace, automotive, marine, and construction industries. However, defects such inclusions and voids may seriously affect the quality of FRP products. Therefore, implementing non-destructive testing to detect defects is necessary.

Among existing non-destructive testing techniques, pulsed thermography (PT) [1] is popular on account of its short inspection times, low cost, wide scanning range, and ease of operation. The underlying principle of PT is as follows. First, an energy pulse is generated using photographic flashes to heat the surface of the specimen to be tested. The heat flux then diffuses to the interior of the material. Meanwhile, the response of the surface temperature of the specimen is captured using an infrared camera, as a time series of thermal images. By investigating these thermal images, the locations of defects can be identified by quality engineers by considering the contrast between normal and defective areas.

However, the quality of thermal images produced by PT is often affected by both measurement and electronic noise. In addition, unavoidable uneven heating introduces non-uniform backgrounds into images, making it difficult to clearly identify defects from the raw thermographic data. Therefore, it is necessary to utilize thermographic data processing methods to analyze the thermal images to improve detection results. Previous research has demonstrated that traditional image processing methods that were commonly adopted in the past, such as absolute thermal contrast (ATC) and image binarization, are not sufficiently effective [2]. In recent years, thermographic signal reconstruction (TSR) [3] has been viewed as a breakthrough in thermographic data processing [4], mainly on account of its noise reduction performance. From the viewpoint of filtering, TSR applies a polynomial filter on each pixel, and smooths the thermographic data in the time direction. However, because TSR treats each pixel separately, the spatial information contained in each image is not exploited in the noise reduction process. The famous multivariate statistical method known as principal component analysis (PCA) [5] has also been adopted for processing thermographic data. The resulting technique is named principal component thermography (PCT) [6]. This method attempts to capture background information using the first empirical orthogonal function (EOF), and retain noise in the EOFs corresponding to small eigenvalues. Thus, the majority of information regarding defects is extracted by the second and third EOFs, based on which

* Corresponding author.
E-mail address: yyao@mx.nthu.edu.tw (Y. Yao).

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improved detection results can be expected. Nevertheless, there is no assurance that PCT can effectively separate different levels of information, even theoretically. In addition to the above-reviewed methods, pulsed phase thermography (PPT) [7] and differentiated absolute contrast (DAC) [8] are also commonly employed. However, the existing literature demonstrates that the performances of PPT and DAC are inferior to that of TSR [9,10]. Most recently, mathematical morphology (MM) [11] and penalized regression (PELS) [12,13] have been utilized for thermographic data processing [14,15]. The cost of the strong performances of these methods is the presence of a large number of parameters that are not easy to adjust.

In this study, a matrix recovery method called stable principal component pursuit (SPCP) [16] is integrated with a moving window strategy, to solve the problems of noise reduction and background removal simultaneously. SPCP decomposes a data matrix into three parts, including a low-rank matrix, a dense noise matrix, and a sparse matrix. When dealing with thermographic data, each two-dimensional thermal image is unfolded into a vector. In this manner, the thermal images recorded within a certain time window are aligned into a matrix, in which each row corresponds to an image and each column corresponds to a pixel point. A defect of certain size and depth is usually reflected by just a few pixels in a small number of thermal images. Consequently, defect signals are regarded to be sparse in the data matrix, and can be extracted by conducting SPCP. Following the decomposition, the resulting low-rank matrix approximately extracts information regarding non-uniform backgrounds, the noise term captures most of the measurement and electronic noise, and the defects are identified by the non-zero elements in the sparse matrix. Thus, the visual detection of defects can be achieved by converting the sparse matrix into a series of thermal images in which noise and non-uniform backgrounds are largely removal. Further details regarding the proposed method are provided in Section 3.

The remainder of this paper is organized as follows. The mechanism of PT is briefly introduced in Section 2. In Section 3, the proposed SPCP-based processing method is described, where TSR is utilized as a pre-processing step, followed by SPCP decomposition of the thermographic data and reconstruction of the thermal images. In Section 4, the proposed method is employed to detect defects in carbon fiber reinforced polymer (CFRP) structures. The experimental results demonstrate the effectiveness of the proposed method through a comparison with TSR and PCT. Finally, conclusions are presented in Section 5.

2. Pulsed thermography

The diffusion of heat through a solid constitutes a complex three-dimensional problem, which is often described by Fourier's law of heat diffusion:

$$\nabla^2 T - \frac{1}{\alpha}\frac{\partial T}{\partial t} = 0 \quad (1)$$

Where ∇ is the three-dimensional del operator; T is the temperature, which may vary with time and position; t is the time index; $\alpha = k/(\rho c)$ is the thermal diffusivity of the solid material; k is the thermal conductivity; ρ is the density; and c is the heat capacity. Assuming that the solid is thermally insulated, homogeneous, isotropic, and semi-infinite in thickness, the one-dimensional simplification of (1) is given by [17]:

$$T(z,t) = T_0 + \frac{Q}{e\sqrt{\pi t}} \exp\left(-\frac{z^2}{4\alpha t}\right) \quad (2)$$

Here, Q is the total energy absorbed by the solid, T_0 is the initial temperature, $e = \sqrt{k\rho c}$ is the effusivity, and $T(z,t)$ is the temperature of the material at depth z and time t.

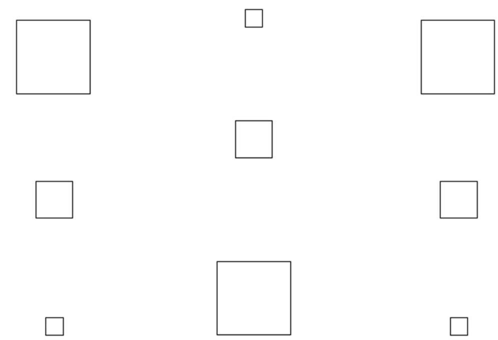

Fig. 1. (Case 1) Illustration of the defect locations.

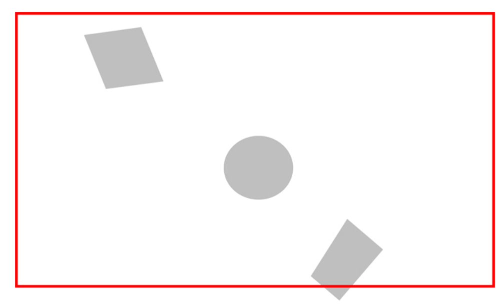

Fig. 2. (Case 2) Illustration of the defect locations.

In PT, only the surface temperature of the tested specimen is recorded by the infrared camera, in the form of a time series of thermal images. In other words, the parameter z in (2) is fixed as 0. Therefore,

$$T(t) = T_0 + \frac{Q}{e\sqrt{\pi t}} \quad (3)$$

This equation describes the surface temperature response at each pixel in the collected thermal images. Following the performance of pulsed heating, the thermal front moves through the specimen as time progresses, resulting in a reduction of the surface temperature. When defects are present, subsurface discontinuities often result in resistance against the heat flow, which then leads to contrasts in the surface temperature between intact and defective regions. Hence, these defects can be located by analyzing the patterns contained in the thermal images.

However, as discussed in the previous section, it is not usually easy to identify the defects from the thermal images by visual inspection, owing to the presence of noise and non-uniform backgrounds. This fact is the motivation for the research presented in this paper.

3. SPCP-based thermographic data analysis

In this section, an SPCP-based thermographic data analysis method is developed. First, TSR is adopted for the pretreatment of the thermal images. Then, the TSR-processed images are organized into data matrices according to a moving-window strategy. Following this, SPCP is employed to decompose the data matrix, resulting in the more effective identification of defects. The details of the proposed method are described below.