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Automatic defect detection based on segmentation of pulsed thermographic images

Kaiyi Zheng, Yuan Yao*

Department of Chemical Engineering, National Tsing Hua University, Hsinchu 30013, Taiwan, ROC

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ABSTRACT

Pulsed thermography, widely used as a nondestructive testing method, offers many advantages for material defect detection. However, most existing methods for pulsed thermographic data processing aim to enhance the defect signals in each single thermal image, whereas automatic defect detection is not achieved. Instead, laborious and time-consuming visual inspection of the processed images is required to draw final conclusions. It is usually impossible to visually inspect all images. Therefore, manual selection of a few informative images is often a required step before thermal image processing, probably resulting in the oversight of necessary defect information. To overcome the drawbacks of the existing methods, a hyper-image segmentation method is proposed in this study, which analyzes all thermographic data simultaneously to achieve automatic defect detection and avoid the risk of losing information. Specifically, an iterative defect detection procedure is designed on the basis of the Laplacian eigenmap algorithm. The results of a case study on the carbon-fiber-reinforced plastic (CFRP) materials show the feasibility of the proposed method.

1. Introduction

In recent years, nondestructive testing (NDT) methods have been widely adopted for the detection of defects in materials. These techniques include thermography [1,2], ultrasonic inspection [3–5], electrical resistance [6], X-ray inspection [7], etc. Among these NDT methods, thermography is particularly attractive and offers the advantages of low cost, easy operation, high speed, and wide area coverage.

Thermography is a subsurface analysis technique that generates a series of thermal images by using an infrared camera to capture the surface temperature of the target specimen. Thermography can be categorized into two classes: passive thermography and active thermography. The passive type is suited to the analysis of samples with inner heat sources, such as biological organisms, furnaces, etc. For composite materials, however, there is no such inner heat source. Thus, active thermography is adopted. An important category of active thermography is pulsed thermography (PT), which uses a high-energy, short-period heat source to heat the surface of the specimen. After heating, the heat diffuses into the specimen. At the same time, the variations in the temperature of the specimen's surface can be captured by an infrared camera to generate a thermographic dataset. Owing to the speed of the inspection, PT is popular in the field of active thermography [8]. According to the locations of the tested specimen, heat source, and infrared camera, the operation of PT can be further classified into two modes: transmission mode and reflection mode. In transmission mode, the external heat source stimulates the tested specimen on one side while the camera captures the temperature information on the opposite side of the specimen. In reflection mode, in contrast, the external heat source and the infrared camera are both positioned on the same side of the specimen. Generally, the former is usually used for detecting defects located near the heated surface, whereas the latter allows detection of defects near the rear surface. However, because the rear face may not be accessible and the defect depth cannot be estimated in transmission mode [9], reflection mode is more widely used in PT. Thus, in this study, we opted to utilize the reflection mode of PT.

As illustrated in Fig. 1, the PT dataset consists of three-dimensional (3-D) data shown as a series (Nt frames) of two-dimensional (2-D) thermal images, each with a size of $Nx \times Ny$ pixels and corresponding to an acquisition time point. From another point of view, the dataset can also be seen as a hyper-image with a size of $Nx \times Ny$, with each pixel corresponding to a temperature decay curve at Nt time points. In PT, differences exist between the temperature decay curves in the defective and intact regions [10] because of the different thermal properties resulting from the discontinuities in the inner structures of the material. Hence, based on the thermal images, the temperature contrasts between the defective and intact regions offer a means of defect detection.

However, in practice, the factors including noise, external environ-

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

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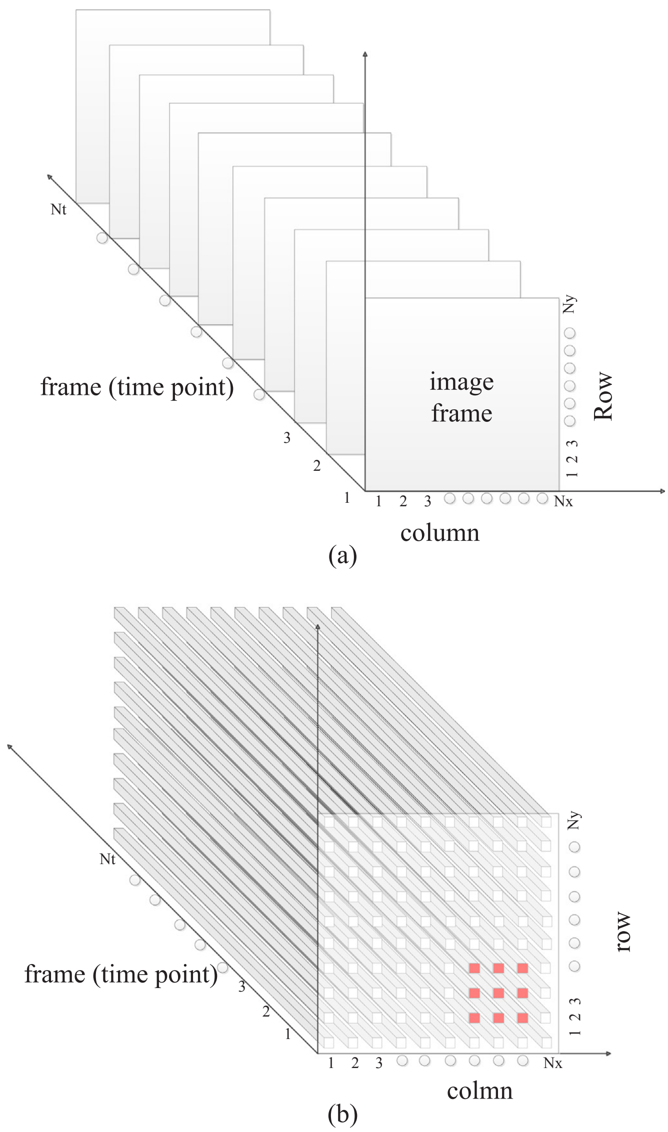

Fig. 1. Structure of 3-D thermographic dataset: (a) shown as a 1-D acquisition time sequence, with each time point corresponding to a frame of a 2-D thermal image; (b) shown as a 2-D image, with each pixel corresponding to a 1-D temperature decay curve (the red ones are example pixels in Fig. 2). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

mental disturbances, and uneven heating may lead to a low level of contrast in the collected thermal images. In attempts to address these issues, PT data processing methods have been proposed, such as thermographic sequence reconstruction (TSR) [11], differential absolute contrast (DAC) [12], pulsed phase thermography (PPT) [13], principal component thermography (PCT) [14], multi-dimensional ensemble empirical mode decomposition (MEEMD) [15], stable principal component pursuit (SPCP) [16], mathematical morphology [17], penalized least square (PELS) [18], etc. Among these methods, the recently proposed PELS is effective at characterizing defects by removing the noise and non-uniform backgrounds contained in the thermal images.

Although these data processing methods enhance the contrast between the defective and intact regions, they cannot localize the defects automatically. Instead, visual inspection of thermal images is the most common way to identify the detect locations based on PT, which is time consuming and laborious. Most recently, image segmentation is implemented in thermal image analysis to achieve more efficient defect detection [19,20]. However, in these papers, only a few thermal images with distinct defect boundaries are manually selected from the entire 3-D thermographic dataset for processing, resulting in several limitations. First, the selection of the representative frames by means of visual inspection is tedious and time consuming. Second, defects with different depths in the tested specimen are often revealed by the thermal images collected at different sampling time points. The manually selected frames may not contain the information of all defects. Third, because the characteristics of a defect may appear in multiple thermal images, analyzing only a few frames in the thermographic dataset may cause important information on that defect to be neglected.

To solve these problems and achieve automatic defect detection, in this study, the concept of a data mining method called Laplacian eigenmap (LE) [21] is utilized to handle all pulsed thermographic images and temperature decay curves simultaneously. The motivation of the proposed method is as follows. As discussed, PT generates a sequence of thermal images which record the temperature contrasts between the defective and intact regions. It is natural to think of using pattern recognition techniques, specifically image segmentation, for automatic defect identification from these images. In [22], it is proposed to solve the image segmentation problem by minimizing a normalized cut criterion. This criterion measures both the total dissimilarity between the different segments as well as the total similarity within each segment. The minimization problem can be solved efficiently by using LE. Inspired by this research work, a hyper-image segmentation method is proposed in this paper for automatic defect identification based on PT data. An iterative segmentation procedure is developed to identify the locations of different defect regions in sequence. In doing this, more accurate and efficient detection results can be expected.

2. Hyper-image segmentation for automatic defect detection

2.1. Laplacian eigenmap dealing with PT data

In this section, the concept of LE is introduced to the analysis of thermal images.

In the first step of the analysis, an adjacency graph is constructed to summarize both the adjacency information of pixels in the thermal images and the similarities among the temperature decay curves. In the adjacency graph, each node corresponds to a pixel in the hyper-image generated by PT, and there is an edge connecting each pair of adjacent nodes. For each pixel, there are no more than eight adjacent nodes. To weight each edge, the similarity between the temperature decay curves on the corresponding pixels is calculated. Following the suggestion in [21], this similarity can be defined using the heat kernel:

$$S_{i,j} = \exp\left(-\frac{dE_{i,j}^2}{\delta}\right), \tag{1}$$

where

$$dE_{i,j} = \sqrt{(\boldsymbol{x}_i - \boldsymbol{x}_j)^T(\boldsymbol{x}_i - \boldsymbol{x}_j)}, \tag{2}$$

$\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are vectors describing two temperature decay curves, and δ is a user-specified scaling parameter.

The adjacency graph is then transformed into a matrix denoted as $\boldsymbol{W}$, where the entries $W_{i,j}$ in $\boldsymbol{W}$ are defined as

$$W_{i,j} = \begin{cases} S_{i,j}, & \text{if } \boldsymbol{x}_i \text{ and } \boldsymbol{x}_j \text{ are adjacent;} \\ 1, & \text{if } i = j; \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Obviously, the value of $W_{i,j}$ of adjacent pixels is located between zero and one.

In the foregoing steps, the parameter δ should be selected with caution, because it determines the resolution of the algorithm. An