Automatic Crack Detection Algorithm for Vibrothermography Sequence-of-Images Data

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AUTOMATIC CRACK DETECTION ALGORITHM FOR VIBROTHERMOGRAHY SEQUENCE-OF-IMAGES DATA

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ABSTRACT. Vibrothermography (Sonic IR, thermosonics) is a technique for finding cracks through frictional heat given off in response to vibration. Vibrothermography provides a sequence of infrared images as output of the inspection process. A fast and accurate automatic crack-detection algorithm for the sequence-of-images data will greatly increase the productivity of vibrothermography method. Matched filtering is a technique widely used in signal detection, and it is the optimal linear filter to maximize the signal-to-noise ratio in the presence of additive uncorrelated stochastic noise. Based on key features from images of known cracks, we can construct a three-dimensional matched filter to detect cracks from the vibrothermography data. In this paper, we evaluate the matched filter developed from a vibrothermography inspection sequence-of-images. The probability of detection for the matched filter detection algorithm is then compared with the probability of detection for a simpler detection algorithm that is based on a scalar measure of the amount of heat generated in an inspection. Our results show the matched filter algorithm provides improved detection capability when a flaw signature is known approximately.

Keywords: Matched Filter, POD, Probability of Detection, Signature, Thermal Acoustics

PACS: 43.60.Uv, 43.60.Cg, 81.70.Cv

INTRODUCTION

Background

Nondestructive evaluation (NDE) methods are widely used in many industries such as aerospace engineering and civil engineering to detect flaws or cracks enclosed in structures by measuring physical responses. Vibrothermography is a method to detect cracks based on the heat generation and temperature increase around the cracks under external excitation of sonic or ultrasonic waves. The output of a vibrothermographic inspection is a sequence-of-images taken by an infrared camera. The sequence-of-images usually starts a short time before the excitation source is turned on and stops a short time after the excitation source is turned off to record the temporal trend of temperature increase and decrease as well as the spatial pattern around the cracks. In this paper, we analyze vibrothermographic inspection data taken on a collection of 63 Titanium Ti-6Al-
4V specimens and 63 Inconel 718 specimens containing fatigue cracks. The purpose of the experiment was to study how to increase the signal-to-noise ratio of the vibrothermography sequence-of-images output. Those Titanium and Inconel specimens were specially fabricated with cracks of known size.

Motivation and Overview

There are many ways to analyze vibrothermography data. For example, Holland et al. [1] developed an algorithm, based on a physical model, to reduce the vibrothermography sequence-of-images data in each experimental measurement into a scalar measure of temperature increase. Li et al. [2] applied a noise interference model to obtain the probability of detection (POD) based on the scalar summary of the sequence-of-images data. Scalar reduction simplifies quantitative comparison of PODs across different inspection systems using the traditional à-versus-a POD estimation methods. The original sequence-of-images data, however, contains more information that can be used to increase detection sensitivity.

In this paper, we apply the statistical idea of a matched filter [3] to the vibrothermography sequence-of-images output, dramatically increasing the signal-to-noise ratio. Then we use the matched filter output to develop an automatic crack detection algorithm. This paper is organized as follows: First we describe the experimental configuration of vibrothermography systems. Then we present the idea of a matched filter in a simple one dimensional (1D) example. Finally we apply the 3D matched filter to the sequence-of-images data and further develop an automatic crack detection algorithm.

Vibrothermography System Setup

The particular vibrothermography inspection system used in our experiments is illustrated in Figure 1 (left). This system involves an excitation source to excite the sample, an infrared camera to record heating of the specimen, and a laser vibrometer to monitor vibration in the specimen. The excitation source (a piezo stack) is pneumatically pressed to the sample, and the sample itself is gripped with a rigid or compliant clamp. A coupling medium, such as paper, plastic, or cardstock is usually used to separate the tip of the vibration source from the sample. The specimen is typically excited for 1 to 2 seconds.

The goal is to cause the crack surfaces to rub and generate heat. The sample surface temperature profile is captured by a sequence-of-images, recorded by an infrared camera and the sample surface velocity is measured by a laser vibrometer. Both the temperature profile and the surface velocity are typically recorded at short time intervals for each measurement. The vibrometer sampling rate was 1 MHz, and the infrared camera sampling rates was 90 Hz.

The piezo stack that is used as excitation sources typically generates 1 to 2 kW of vibrational power at a fixed frequency such as 20 kHz. For this study the specimens had been tuned to a natural resonance near 20 kHz. During an inspection, the vibrational excitation power was coupled into the specimen near the natural resonance and the frictional rubbing between crack surfaces generated heat.
FIGURE 1. The vibrothermography system experimental setup (left) and a typical spatial pattern at the frame with maximum temperature for a relatively large crack (right).

Figure 1 (right) shows a particular frame of the sequence-of-images data for a relatively large crack when the temperature is the largest. We can clearly see the higher temperature at the center of the picture compared with the surrounding areas, and there would be no problem detecting the existence of crack from the sequence-of-images of that particular specimen. In real applications, however, it is important to identify relatively small cracks, possibly monitoring the crack growth behaviors starting from relatively small cracks, and then repair or replace the part when the crack is larger than the preset criterion. For small cracks, the signal within the sequence-of-images is usually buried under noise and we cannot easily identify the existence of cracks, and statistical ideas to boost signal-to-noise ratio become essential to setup crack detection criteria and for an automatic crack detection algorithm.

CONCEPT OF MATCHED FILTER

Matched filters are widely used in signal processing to increase the signal-to-noise ratio. A matched filter is the optimal linear filter in terms of signal-to-noise ratio under a stationary white noise process. [3] One requirement for using a matched filter is that we have to construct the matched filter based on the knowledge of the signal signature. An introduction to the concept of a matched filter can be found in [3]. First we show conceptually how a matched filter works in a simple one dimensional case.

Suppose the 1D signal we are expecting to receive is represented by a set of discrete data points \( h[k], k = 1, ..., 50 \) as shown by the red dots at Figure 2 (left). The 1D white noise is represented by green squares and the actual measurement (signal plus noise: \( x[k], k = 1, ..., 50 \)) is represented by blue triangles. By looking at Figure 2 (left) only, it is difficult to distinguish between the signal plus noise (blue triangles) data and noise only data (green squares), especially when the noise is high. The matched filter utilizes the information of the signal to be received to increase the signal-to-noise ratio by computing the convolution: 

\[
y[j] = \sum_{k=-\infty}^{\infty} h[j-k] \cdot x[k]
\]

where \( x[k] \) is the raw data (which could be either signal with noise or noise only) and \( h[j-k] \) is the reversed known signal (i.e. the filter).
The matched filtered results for signal plus noise (blue triangles) and pure white noise (green squares) at Figure 2 (left) are shown at Figure 2 (right) with the same symbol representation. The matched filtered result for pure signal is shown at Figure 2 (right) as well by red dots. There is a significant difference between the signal plus noise and the pure noise, but there is little difference between signal plus noise and pure signal. By applying the matched filter, the signal-to-noise ratio for actual measurement is increased dramatically. The best discrimination occurs at time sequence 50, just after all the information has entered the filter convolution. With the matched filtered results, reliable automatic classification rules can be developed to separate measurement with signal and measurement of pure noise.

One can extend this 1D matched filter to higher dimensions such as 2D for image analysis and 3D for our sequence-of-images data analysis. As illustrated in Eq. (1), the known signal signature $h[k_1, k_2, k_3]$ and the data $x[k_1, k_2, k_3]$ are now three dimensional arrays. The matched filter is represented by the reversed 3D signal $h[-k_1, -k_2, -k_3]$ and the convolution is now a three-folder summation.

$$h[k_1, k_2, k_3], \quad k_1 = 1, ..., n_1; k_2 = 1, ..., n_2; k_3 = 1, ..., n_3$$

$$x[k_1, k_2, k_3], \quad k_1 = 1, ..., n_1; k_2 = 1, ..., n_2; k_3 = 1, ..., n_3$$

$$h[n_1-k_1, n_2-k_2, n_3-k_3], \quad k_1 = 1, ..., n_1; k_2 = 1, ..., n_2; k_3 = 1, ..., n_3$$

$$y[j_1, j_2, j_3] = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \sum_{k_3=-\infty}^{\infty} h[j_1-k_1, j_2-k_2, j_3-k_3] \cdot x[k_1, k_2, k_3]$$

$$j_1 = 1, ..., 2n_1; j_2 = 1, ..., 2n_2; j_3 = 1, ..., 2n_3$$

Eq. (1)

For large matrices, the three-fold summation for the convolution is computationally intensive. Fortunately, the Fast Fourier Transformation (FFT) can be used instead to reduce the computation time dramatically. For our sequence-of-images data, the whole computation time to finish one matched filter calculation is less than 10 seconds with FFT.
APPLYING MATCHED FILTER TO SEQUENCE-OF-IMAGES DATA

In this section, we show how to apply a 3D matched filter for our sequence-of-images data. Then we show how to use the output of the matched filter as input to an automatic detection rule and compare POD before and after matched filter.

To construct a 3D matched filter for the sequence-of-images data, we need to describe the temperature change for both the temporal trend and spatial pattern with the presence of a crack. Two approaches can be adopted to get the temperature change: (1) from empirical measurement result with relatively clear temperature change and (2) from the underlying heat dispersion theory to find the analytical temperature change function. We use the empirical results for the temporal trend (Figure 3 left), and use the analytical 2D Gaussian peaks for spatial pattern (Figure 3 right). The combination of temporal and spatial character together can provide a 3D matched filter. We have found that the outputs of the matched filter are not sensitive to such small changes in the matched filter.

**FIGURE 3.** The expected signal in the sequence-of-images data: The empirical temporal trend (left) and simulated Gaussian kernel spatial pattern (right).

**FIGURE 4.** The highest contrast 2D image slice of our 3D sequence-of-images data before applying matched filter (left) and after matched filter (right).
FIGURE 5. Three criteria for a crack-existence decision: (1) global maximum value (cross, left), (2) signal-to-noise ratio (between the two boxes, left), and (3) time index to reach the global maximum (points, right).

The highest contrast 2D image for the sequence-of-images data is shown at Figure 4 (left), and the highest contrast 2D image after the matched filter is shown at Figure 4 (right). By looking at the raw data, it is hard to locate a “hot spot”. The “hot spot” is, however, clearly present in the image after the matched filter. We propose three different crack detection criteria based on examination and comparison of the matched filter results from all sequence-of-images data with cracks and without cracks: (1) The global maximum value in the whole 3D data after the matched filter as indicated by a cross in Figure 5 (left); (2) The signal-to-noise ratio calculated by taking the ratio between the average value of the pixels in the small square and the average value of the pixels between the small and large square shown at Figure 5 (left); and (3) the time index for the local maximum in each 2D image to reach the global maximum shown at Figure 5 (right). The frame index 150, shown as the vertical solid line at Figure 5 (right), is the moment when all frames of sequence-of-images are included in the convolution computation. For most of the data with cracks, the time index is less than 150; while for most of data without cracks, the time index is more than 150. We define the time index to be zero if the global maximum happens at time frame 150, and the time index is positive if the global maximum happens before time frame 150.

The relationship between data sets with a crack (filled symbols) and data sets without crack (open symbols) as functions of the three criteria are illustrated at Figure 6. Most data without cracks are located at the bottom-left corners (region B) at Figure 6 with smaller global maximum value, smaller signal-to-noise ratio, and negative time index to reach global maximum. The detection thresholds at Figure 6 are represented by horizontal and vertical dashed lines: 50 for global maximum value, 8 for the signal-to-noise ratio and 0 for time index of reaching global maximum. Based on such detection thresholds we can construct an automatic crack detection algorithm: a crack existence decision will be made if the data points are in region A for both graphs at Figure 6; a non-crack existence decision will be made if the data points are in region B for both graphs at Figure 6; and a further investigation decision will be make if the data points are in region C for any of the two graphs at Figure 6. Further investigation requires an experienced operator to look at the original and matched filter results carefully to make final decision with possible new measurements. Through the automatic crack detection algorithm, we can dramatically...
reduce the number of sequence-of-images that the operators need to watch each day. We are currently at the stage of optimizing the detection threshold for automatic crack detection.

**POD COMPARISON BEFORE AND AFTER MATCHED FILTER**

The widely used performance metric in nondestructive evaluation is probability of detection (POD) [4]. POD characterizes the performance of a particular inspection method as a function of crack size. To get the traditional \( \hat{a} \)-versus-\( a \) POD for sequence-of-images data, a scalar measure of heat increase is extracted from each sequence-of-images data [1,2]. To compare the POD before and after applying the matched filter, we need a scalar
summary of data after matched filter as well. The maximum global value and the signal-to-
noise ratio are good choices for the scalar reduction. Figure 7 (left) shows the relationship
between the global maximum values and crack sizes in logarithm-logarithm scale and the
regression line without the three sets of data from the largest cracks. For extremely large
cracks (i.e. larger than 100 mils) the heat generation follows different mechanisms and this
can lead to different behaviors of the global maximum values, and thus those three sets of
data were removed from the regression. The relationship between the signal-to-noise ratio
and crack size is similar to that shown in Figure 7 (left) and it is not shown in this paper.
After the regression relationships have been estimated from the data, POD as function of
 crack size can be obtained as described in [4]. The estimated POD for heat increase, the
global maximum value and the signal-to-noise ratio are compared at Figure 7 (right). Both
the global maximum value and the signal-to-noise ratio from the matched filter data have
high POD for all crack sizes than the POD from heat increase based on the original
sequence-of-images data.

CONCLUSIONS

In this paper, we apply a matched filter to the vibrothermography sequence-of-
images data to increase the signal-to-noise ratio assuming that we have knowledge of the
heat change signature in the present of cracks, at least approximately. Using a FFT, the
matched filter computation time is less than 10 seconds, and almost instantaneous results
can be obtained for any of the sequence-of-images data sets. Based on the data after
matched filter, an automatic crack detection algorithm has been developed to reduce the
operator’s work load. The probability of detection based on the scalar reduction of
matched filtered data is higher for all crack sizes than the original sequence-of-images
data.

Future work includes optimizing the automatic crack detection algorithm,
quantifying statistical error on the POD estimate, and extending the matched filter
technique to other inspection methods or data sets where image analyses are used.

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