Inductive Thermal Nondestructive Evaluation:
Multi-dimension Pattern Interpretation and Separation

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Abstract. This paper presents methods of unsupervised thermal pattern mining-enabled imaging methods and applies it to the research field of nondestructive testing and evaluation. The issue of automatic defects identification has not been fully addressed by researchers and it marks a crucial first step to analyzing the structural health of the material, which in turn sheds light on understanding the production of the defects mechanisms. In this study, we bridge the gap between the physics world and signal processing world. This is a first step towards realizing the automatic of defect identification. In inductive thermography, a series of multi-dimension pattern mining methods are developed to extract anomalous patterns from transient thermal videos under different condition. We will show that these methods can efficiently locate the defects in the spatial-, time- and frequency-domains. In this paper, we will clarify and justify the existence of these thermal pattern separation algorithms from both the mathematical and physics perspectives. Experimental tests on man-made metal defects and natural defects with complex geometry have been selected as example to show the validation of pattern separation.

Introduction

A review of current literature shows that thermography is applicable to a wide range of materials [1] in non-destructive testing and evaluation. Inductive thermography, especially of Eddy Current Pulsed Thermography (ECPT) has been attempted in previous studies, such as penetration depths measurement in metallic materials [2], small defects detection and so on. All these works, however, are limited on manually selecting the proper contrast frames. The information richness of Thermography transient pattern has attracted a wide interest. Several transient response features have been used as an indicator of defect status, which is critical for acceptance/rejection decisions for maintenance and lifetime prediction. To enhance the flaw contrast and improve noise rejection qualities, pattern based image sequences processing has been conducted by introducing the raw data upon a set of orthogonal basis functions. Fourier transform [3] based frequency pattern extraction methods have been applied to pulsed thermography, and enhanced the flaw-contrast significantly by using phase map. Thermographic signal reconstruction (TSR) is a processing technique that improves spatial and temporal resolution of a thermogram sequence [4]. In addition, Principal Component Analysis (PCA) and Independent Component Analysis (ICA) [5] based pattern extraction algorithms are used to improve the flaw detectivity of thermography.
Most of the above mentioned methods, however, employ only the feature extraction transform methods as a signal processing tool. The mathematical reasons why these algorithms can enhance the flaw contrast and how the procedures links to physical model are not given. The results are acceptable but generally not predictable. The proper contrast components have to be empirically selected. This ambiguous case prevents the use of thermography in automated environments. For ECPT, when the eddy current encounters a discontinuity e.g. a slot or notch, they are forced to divert, leading to areas of increased and decreased eddy current density [5]. Therefore in the heating phase, different areas have different heat generation rates. Hot spots are observed around the slot tips and the cool areas locate at both sides of the slot. The spatial temperature of these areas cannot be directly obtained or viewed through sensors but can be considered as the pattern regions which have different distribution characteristic of eddy current density, this will result in different spatial temperature regions. These regions are considered as the pattern thermogram (PT) which is mixed in observation mixture image (IR camera). In this paper, Multi-dimension of spatial-, time- and frequency-based on pattern separation is developed to extract abnormal patterns from transient thermal videos. This method can automatically highlight the defects in both the spatial, time and frequency domains. The mathematical foundation for abnormal image identification is also presented.

Methodology

1.1 Pattern Interpretation and Mixing Model

In this paper, a finite in length but extending completely through the sample slot is considered as an instant to describe the thermal pattern interpretation. The resultant heating frame from ECPT (0.1s) is presented in Fig. 1 bottom panel. In the heating phase (before 0.1s), different heat generation rates enlarge the temperature spatial variation. Hot spots are observed around the slot tips and the cool areas locate at both sides of the slot. In the cooling phase (after 0.1s), heat diffuses from high temperature area to low temperature area, and reduces the contrast. In addition, the area which is located far away from excitation coil will continually rise in temperature because of heat diffusion. In the cooling phase, the heat diffuses from the high temperature area to the low temperature area, and reduces the thermal contrast. In addition, the samples under test possibly have oil, oxide and other stains on the surface, this inevitably suffer from the strong interference of emissivity. These different areas can be considered as the pattern regions which share the similar transient responses in the sample. The infrared camera functioned as a temperature spatial image signal recorder along with time flowing. In this case, as only one camera exists, this refers to ‘single channel’. In addition, the camera actually records the mixed image signal corresponding to the signal image from the pattern regions at each time point. This can be seen in Fig 1. To avoid the influences of arbitrary selection of image frame from the transient thermal videos, extraction of abnormal patterns has become ever more crucial. Therefore, the task of the proposed method is to blind separate the observed signal image sequence into pattern images as well as their corresponding transient response and automatically identify the one which relates to defects. Fig. 1 bottom panel shows the different characteristic of transient responses at the various positions chosen from the pattern regions. Specifically, it can be seen in Figure 1 and 2, position 1 represents an independent region $x_1(t)$ with high rising and high falling rate of temperature; position 2 represents an area $x_2(t)$ with moderate rising and falling rate; position 3 represents an independent region $x_3(t)$ with high rising rate followed by a continually low speed rising and then drop down; and position 4 represents an independent region $x_4(t)$ with continually temperature increasing.
Mathematically, the thermography image captured by the infrared camera is considered as a mixing observation signal image $Y(t)$. The term $m_i$ is the mixing parameter which describes the contribution of the $i^{th}$ position to the induced recorded thermography image in Fig. 1. In real applications, the number of independent areas $N_i$ is not necessarily limited to 4. As there is only one infrared camera in ECPT, this leads to the single channel source separation problem. The mathematical model [5] can be described as:

$$Y(t) = \sum_{i=1}^{N_i} m_i X_i(t)$$  \hspace{1cm} (1)

where $N_i$ denotes the number of independent signal image areas. $Y(t)$ and $X_i(t)$ denote the recorded image and the independent image generated by the area of position $i$ at time $t$ with dimensional $N_x \times N_y$, respectively. In this study, $N_x \times N_y$ are defined by the infrared camera sensor array. Eq. (1) is the special case where $N_i = 1$ ($N_i << N$ one camera). To solve the ill-posed problem, we adopt a decomposition-based approach. The approach is used for analyzing non-stationary signals by expressing a fixed-length segment drawn from transient response, such that continuous transient slices of length $N$ can be chopped out of a set of image sequences from $t$ to $t+N-1$, and the subsequent segment is denoted as equivalent as image sequences captured by $N$ observations $Y' = \begin{bmatrix} \text{vec}(Y(t)), \text{vec}(Y(t+1)), \ldots, \text{vec}(Y(t+N-1)) \end{bmatrix}^T$ where $\text{vec}^T$ denotes transpose operator and $\text{vec}$ denotes the vectorize operator. The constructed image sequences is then expressed as a linear combination of different thermal patterns such that

$$Y' = MX'$$  \hspace{1cm} (2)

where $M = \begin{bmatrix} m_1, \ldots, m_{N_i} \end{bmatrix}$ is the mixing matrix, $m_i$ is the $i^{th}$ mixing vector and $X' = \begin{bmatrix} \text{vec}(X_1(t)), \text{vec}(X_2(t)), \ldots, \text{vec}(X_{N_i}(t)) \end{bmatrix}^T$. Assuming that $N_i = N$ and $M$ has full rank so that the transforms between $Y'$ and $X'$ be reversible in both directions such that we can find the inverse matrix $W = M^{-1}$ which refers to the blind pattern separation methods. The purpose of this decomposition is to model the multivariate distribution of $Y'$ in a statistically efficient manner.

The phase information of thermography has been proved to offer deeper thickness of probing under the surface, less sensitivity to optical and infrared specimen surface features, better defect shape resolution, non-necessity to know a priori position of a non-defect area in the field of view to compute...
contrast image, ability to inspect high thermal conductivity specimens. In particular, the magnitude thermal image is proportional to local optical and infrared surface features. Of significant interest then is the phase image which being related to the propagation time delay, is independent of optical or surface features. Besides the spatial-time thermal pattern modeling, the spatial-frequency thermal pattern modeling is also investigated by computing the Discrete Fourier Transform (DFT) for each transient response:

$$\tilde{Y}_n(f) = \Delta t \sum_{n=0}^{N-1} Y_n(n\Delta t)e^{-j2\pi n\Delta t} = R_n(f) + iI_n(f)$$

where, $\Delta t$ is the sampling time step, $R_n(f)$ and $I_n(f)$ are the real and imaginary components of $\tilde{Y}_n(f)$, respectively. The subscript $x$, $y$ are the coordinate index of spatial $x$ and spatial $y$, respectively. The spatial-phase spectrum from the phase thermography can be calculated as $\Phi_{xy}(f) = \tan^{-1}(R_{xy}(f)/I_{xy}(f))$ across the $x$- and $y$-axes. The observed spatial-phase spectrum is a sum of contribution from thermal events given by $\Phi_{xy}(f) = \sum_{i=1}^{N_y} m_i X_i(f)$. Similar to time domain analysis, thermography spatial-phase image $\Phi_{xy}$ in Eq. (2) is a 3-D tensor representation when taking in all $(x, y, f)$ elements. Nonetheless, we can form a 2-D matrix format of the spatial-phase spectrum as $\Phi = \begin{bmatrix} \text{vec}(\Phi_{xy}(0)), \text{vec}(\Phi_{xy}(1)), \ldots, \text{vec}(\Phi_{xy}(N - 1)) \end{bmatrix}^T$.

Then, pattern separation is to factorize the spatial-phase matrix $\Phi$ into a product of two matrices as

$$\Phi = M^f X^f$$

1.2 Pattern Separation

To avoid the influences of arbitrary selection of image frame from the transient thermal videos, the task of the pattern mining is to blind separate the observed $Y$ and $\Phi$ into different characteristic patterns $X^f$, $X^f$ and automatically identify the one which relates to defect. There exists several criteria for mining purpose such as principal component analysis which emphasis the uncorrelation of separated patterns or independent component analysis where the separated patterns are said to be statistically independent [6]. The part-based patterns separation can be achieved by using nonnegative matrix factorization [7] as well as sparse factorization [8] and multiple tensor factorization [9]. The brief steps of pattern mining procedure can be summarized in the Figure 2.

Fig. 2. Schematic illustration of the spatial, time, frequency thermal pattern mining.
Experimental Setup and Results Discussion

1.1 Sample Preparation and Experiment Setup

The experimental setup is shown in Figure 3 and 4. An Easyheat 224 from Cheltenham Induction Heating is used for coil excitation (380 A_{rms} current and excitation frequency 256 kHz are used in this study). Water cooling of coil is implemented to counteract direct heating of the coil. The IR camera, SC7500 is a Stirling cooled camera with a 320 × 256 array of 1.5-5μm InSb detectors. In this study, 2s videos are recorded in the experiments. A rectangular coil is constructed to apply directional excitation. This coil is made of 6.35 mm high conductivity hollow copper tube. A steel sample (0.24×45×100 mm$^3$) with a slot of 10mm length, 2mm width was prepared, as shown in Figure 3a. Thermal conductivity of the stainless steel is 14Wm$^{-1}$K$^{-1}$. There are equally spaced shining and black stripes with 5mm width on the sample surface. The shining strips are the polished area, while the black strips are the area sprayed with black painting. They illustrate different emissivity. The emissivity of the black region is 1, which is the same for a blackbody. While, the emissivity of the shining stainless steel surface is about 0.16. In the experiments, coil and IR camera were placed on the opposite side, presenting transmission mode. The coil was perpendicular to the slot and across the slot centre. For natural defects validation, a steel blade sample provided by Alstom is also investigated in this study (Fig. 4). In the blade, flaws are produced in-situ with controlled thermal fatigue loading. The flaws grow with natural thermal fatigue damage mechanism. In this study, one natural crack: 167BBB1361 is detected. The crack location is marked with red circles in Fig. 4 (b). Crack 167BBB1361 is 4.2 mm length and coupled with a secondary crack. A 200 ms heating duration is selected for inspection.

![Experimental Setup](image)

**Fig. 3.** (a) ECPT platform (b) Test sample (c) Original recorded infrared image at 0.1s (the end of heating phase) (d) Transient responses of different positions.
1.2 Results Discussion

Figure 3c shows the temperature distribution at the end of heating (0.1s). Due to the high emissivity of the black area, there is no obvious high temperature region around the slot tips. The high temperature can only be observed at the black area above the coil. The high temperature still can only be observed at the black strip area because of both high emissivity and heat diffusion. The transient temperature behavior at different positions is shown in Figure 3d. Pos 1 is at the crack side with black strip (high emissivity), Pos 2 is at the black strip where the area is far away from the excitation, Pos 3 is at the crack tip with the shining strip, Pos 4 is at the crack side with shining strip above the coil. As can be seen in Figure 3d, different position behaves with different temperature transient characteristics. However, Pos 1 as well as other similar black strip area (above the coil) exhibits extreme high temperature transient in both heating and cooling phases in which other thermal patterns have been over-shadowed and therefore, they cannot be distinguished. Both transient and frequency domain are difficult to tackle in defect detection using the thermography method where the hot spot around defect tips cannot be taken as an indicator of defects especially for small cracks. Notwithstanding this, it will lead to error when both black stain and cracks are present on the surface of the test sample. In order to solve this issue, the thermal pattern separation method is conducted. Figure 5 shows the pattern separation results. Figure 5 shows the results by setting the number $N$ of thermal patterns equal to three and using independent component analysis as the thermal pattern mining algorithm. Figure 5a to Figure 5c and Figure 5d to Figure 5f are the separation results by using the spatial-time and spatial-frequency domain pattern separation, respectively. The separation results highlight three complementary thermal patterns: Figure 5a and Figure 5d highlight the cool area with black strip (emissivity). The transient characteristic of this area is similar Pos 1 which can be seen in Figure 3e. Specifically, both separation methods have exhibited their ability to obtain the pattern of cool area. The phase domain separation performs better since the separated pattern using the time based separation somehow still retains the hot spots around the tips. Figure 5b and Figure 5e highlight the hot spots where the transient characteristic of this thermal pattern is similar to Pos 3. In comparison, the spatial-frequency separation has fully recovered both sides of the hot spots and reduced the interface contrast. However, the time domain separation also recovers both sides of a hot spot but still mixes with stronger interface. Figure 5c and Figure 5f highlight the area with black strip (emissivity) besides the excitation coil. The transient characteristic of this thermal pattern is similar to Pos 2. In comparison, the time domain separation does not completely separate this pattern and still mixes the patterns of both black strip and shiny part.
For natural sample testing, two thermal fatigue cracks (a 4.2 mm length crack coupled with a secondary crack on the left) in steel blade are employed for testing. Fig. 4 shows the Penetrate Test (PT) image provided by Alstom and ECPT image at 0.1 s. In the PT image, the area of cracks is marked with red circle. The big crack can be visually identified, while the secondary one is blurred. In the ECPT image, hot spots are shown. This phenomenon indicates that there exist cracks in the sample. However, the cracks are difficult to be quantified. Fig. 6 shows the results processed using pattern separation method. It is noted that Fig. 6b and 6d highlights the defect free area, while Fig. 6a and 6c highlights 4 tips of the two cracks: two big ones on the right correspond to the tips of the big crack, and two small ones corresponds to the tips of the secondary crack on the left. In spatial-frequency domain, the thermal patterns gives more sharp shape resolution and it behaves more sensitivity for surface big cracks. This can be evident in Fig. 6c, the contrast of thermal pattern between hot tips and nondefect region gives higher resolution and bring benefits for crack detection. However, for shorter cracks, the thermal pattern is blued and mixed with bigger one, this will results false alarm in detection.
Spatial-time thermal patterns

Spatial-frequency thermal patterns

Fig. 6. Mining thermal patterns using (a)-(b) spatial-time domain pattern separation, (c)-(d) spatial-frequency domain pattern separation

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