

Research Paper

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Non-invasive inspection for a hand-bound book of the 19th century: Numerical simulations and experimental analysis of infrared, terahertz, and ultrasonic methods

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ABSTRACT

Due to fungal growth and mishandling in the book, there are various types of defects as they age such as foxing, tears, and creases. It is important to develop novel non-invasive inspection techniques and defect recognition algorithms. In this work, three non-invasive inspection techniques, including infrared thermography (IRT), terahertz time-domain spectroscopy (THz-TDS), and air-coupled ultrasound (ACU), were employed for the detection of defects in an ancient book cover. To improve the image quality and defect contrast, principal component analysis, fast Fourier transform, and partial least squares regression algorithms are used as the post-processing methods. Furthermore, the YOLOv7 network is deployed for defect automatic detection. Finite element analysis and finite-difference time-domain methods were employed for generating training dataset of YOLOv7 network. Experimental results demonstrate that IRT and THz-TDS has excellent detection capability for surface and subsurface defects, respectively. By employing YOLOv7 network with simulation datasets, defects can be effectively identified.

Keywords: Hand-bound book; infrared; numerical simulation; terahertz; ultrasound.

1. Introduction

Non-invasive inspection techniques are commonly employed to detect those defects in cultural relics and ancient objects that are not visible to the naked eye while keeping further damage to the test subjects to a minimum level. With the consensual recognition of the importance of the preservation and protection of humanity's history, culture, and artistic heritage, non-invasive inspection has hitherto been receiving increasing attention [1-5]. Indeed, even with the most stringent conservation measures, cultural heritage, such as architectural heritage, old paintings, books, would still inevitably develop cracks, holes, and other forms of defects with the passage of time [6]. On this point, the query of interest is whether those defects can be detected and restored at the

earliest possible time. As timeliness places high requirements on non-invasive inspection regarding sensitivity and accuracy, the hybrid inspection techniques have emerged.

Infrared thermography (IRT) has been repeatedly confirmed as an effective non-invasive inspection technique for cultural heritage by many former works [7-9]. Its working principle resides in using an infrared camera to capture the temperature difference caused by external excitation on the sample surface. Naturally, IRT is suitable for shallow and surface defects, whereas its ability to detect defects deeper into the test subject remains weak. To give perspective on the application of IRT, two examples are summarized. Mercuri et al. [10] applied

IRT to detect marks left by some cold workings used for the surface re-modeling of bronze artifacts cast by the lost-wax technique. The result showed that IRT could reveal detachments of golden leaves even when the defect is non-visible at the surface. Tortora et al. [11] performed IRT and nuclear magnetic resonance relaxometry (NMR) to evidence defects related to the degradation of an ancient book cover. NMR moisture content evaluations and the statistical analysis of IRT data showed that the defective areas are both sub-surface and structurally dysfunctional, which confirms our former claim regarding the applicability of IRT.

Beside IRT, classical ultrasonic testing (UT) has also been widely used in industrial inspection, owing to the strong penetration of ultrasound and simple configuration of UT systems [12]. However, as the waves need to traverse across the sample under test, classical UT is required to submerge the sample in water or other fluids, rendering it unsuitable for inspection of cultural heritage. To remove such dependence on a liquid medium, the air-coupled ultrasound (ACU) technique has been developed in recent years [13]. For instance, Zhang et al. [14] used transmission mid-wave infrared vision and ACU to investigate two paintings on canvas made from different textile support materials. Fernandes et al. [15] applied ACU, X-ray micro-tomography, and IRT to inspect a decorative marquetry sample. The comparative results from three techniques illustrated that X-ray micro-tomography could reveal the defects with most details, and IRT could also provide somewhat

insightful information. Still, the economical and convenient experimental setup is more attractive than X-ray.

The above-mentioned work by Fernandes et al. [15] suggests a comparison of different non-invasive inspection techniques for defect detection, as each technique may be more or less advantageous in some respects as compared to its peers. Terahertz time-domain spectroscopy (THz-TDS) is a novel non-destructive testing technique commonly used in medical imaging, materials characterization, and security testing [16-20]. For instance, Picollo et al. [21] used a portable THz-TDS imaging system to acquire THz images on a laboratory panel painting. However, its applications in defect detection of cultural relics are scarce, with only existing works [22-24].

Automatic defect recognitions (ADR) have been shown to be promising in cultural heritage. Among them, machine learning plays a critical role in ADR such as support vector machines (SVM) [25] and decision trees [26]. However, due to their low efficiency on large datasets, they take long time to train and test. Recently, the deep learning network YOLO (you only look once) is becoming increasingly popular since its high accuracy for complex and high dimensional data. In this work, three non-invasive inspection techniques including IRT, ACU, and THz-TDS were used for inspecting an ancient book cover. Principal component analysis, fast Fourier transform, and partial least-square regression methods were employed for improving image quality and defect contrast. Finally, the YOLOv7 network was chosen and trained by

simulation datasets from finite element analysis and finite-difference time-domain.

2. Research aim

Summarizing the discussion thus far, this research should wish to focus on using non-invasive inspection for defect detection in an ancient hand-bound book cover. The first contribution of this work is that it compares several non-invasive inspection techniques including IRT, THz-TDS, and ACU, which has rarely been performed in this field. Next, in order to reduce the noise embedded in the original images and thereby extract useful information for detection, three commonly used image processing methods, namely, PCA, FFT, and PLSR are employed. Finally, an automatic object recognition algorithm based on one of the latest proposed deep-learning networks, that is, YOLOv7, is used to realize automatic defect detection. As mentioned earlier, training deep networks often depends for its success upon the amount and quality of input data, but it is hard to acquire enough experimental results since defect detection constitutes a small-sample problem. To mitigate this challenge, a model for the book cover is constructed in COMSOL software with finite-difference time-domain (FDTD) method to generate a simulated dataset that can support the training of deep-learning models. The test results show a significant application potential for automatic inspection of defects in cultural heritage.

3. Experimental setup and sample description

3.1. Experimental setup

The first imaging technique to be discussed is IRT, which has the advantages of good sensitivity, higher resolution, and advanced data processing technology. However, IRT cannot be considered an optimal imaging technique. Instead, it requires external excitation, such as electromagnetic, optical, or vibration, to reveal richer features than passive thermography. To avoid contact and uneven heating, optical pulsed thermography (OPT) technology has been chosen to test the sample. Fig. 1 shows the experimental setup of the OPT system herein constructed. Two flash lamps (Balcar FX60, 6.4 kJ power, 2 ms duration) are used to provide optical flashes. A mid-wave IR camera (FLIR Phoenix, ~55 Hz frame rate, 25 mK noise equivalent temperature difference) is adopted to record the temperature profile of the test subject. The cooling time is set as 10 s for the flash lamps. The resolution of the camera is 640 x 512 pixels, the detector is of size 25 μm x 25 μm , and a 50-mm lens employed provides a field-of-view of 18.2° x 14.6° along the horizontal and vertical positions, respectively.

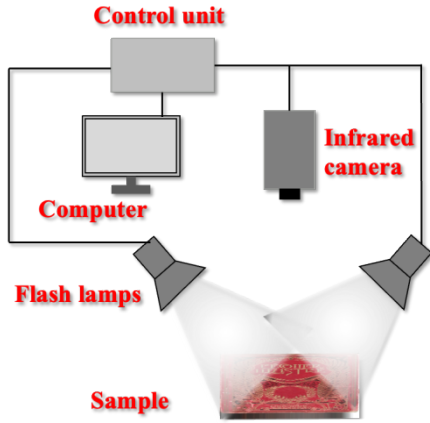


Fig. 1. Experimental setup of OPT.

The THz-TDS technique is a novel non-invasive inspection based on the strong penetration and high resolution of terahertz wave, which is a kind of electromagnetic wave with a frequency of 0.1 to 10 THz (3000 to 30 μm). Fig. 2

shows the experimental setup for THz-TDS. The ultra-fast laser pulse is split into a pump beam and a reference beam. The pump beam is time-shifted using an optical time-delay line and then adapted to excite a THz pulse through a THz emitter. The THz wave traverses across the sample and is detected by a coupled detector. The reference beam is implemented here on the detector as the sampling signal. The THz signal after sampling is transferred to a lock-in amplifier. Amplification of the weak signal is carried out for data acquisition. The THz-TDS system is manufactured by Menlo Systems GmbH, Munich, Germany. The system has a 1.2-GHz frequency resolution and a repetition rate of 100 MHz. Experiments have been performed in transmission mode. The scanning step is set as 0.5 mm.

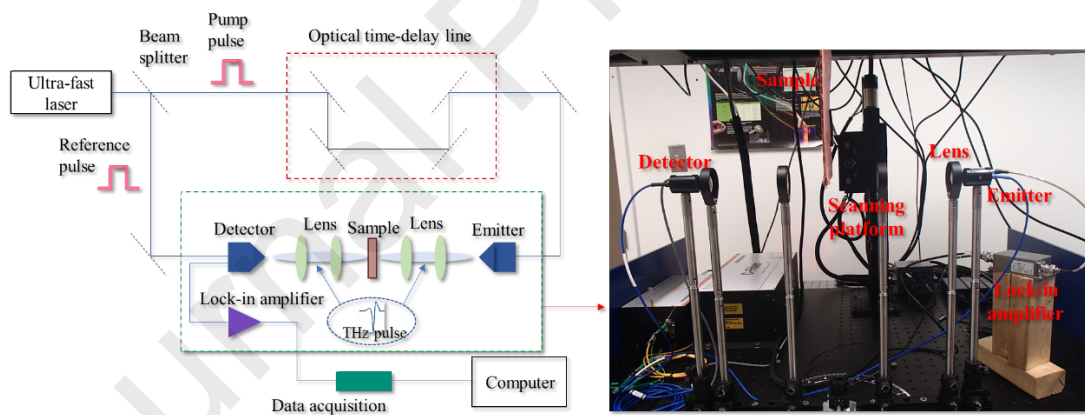


Fig. 2. Schematic (left) and experimental setup (right) of the THz-TDS system.

Lastly, the ACU setup is briefly discussed. It should be again reminded that the classical ultrasonic C-scans often need to be carried out in water tanks, as to obtain great coupling between transducers and tested samples, indicating contact and a risk of water

penetration in the sample. A recent technique leverages a novel air-coupled transducer, thereby frees the sample from the contact with water. This is an important achievement in non-invasive inspection, which even makes possible the performing of tests on non-

waterproof materials, such as the sample of this work. The experimental setup used for the ACU in impulse-echo mode is shown in Fig. 3. An ultrasound transducer emits a high-frequency sound wave into the air. The sound wave travels through the air and the sample, a portion of the sound wave is reflected back towards the transducer. It is noted that the transducer in air-coupled ultrasound acts as both a sound wave emitter and a receiver. Final experimental results are obtained by scanning the sample point by point. The sample rate is 20 MS/s, and the probes are 580 kHz focusing. Exciting sound waves are reflected by the sample.

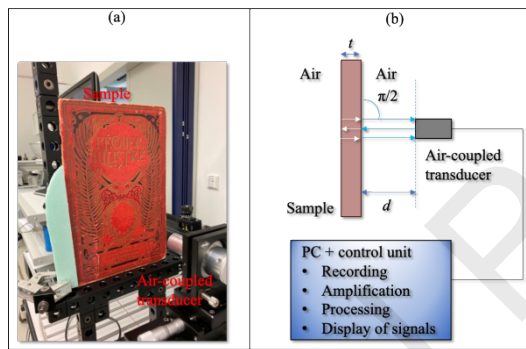


Fig. 3. Experimental setup of ACU system: (a) photograph; (b) schematic diagram.

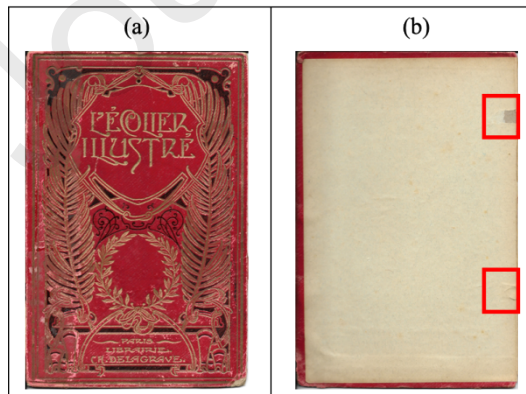


Fig. 4. Photographs of the hand-bound

book cover: (a) the front side; (b) the back side. Inserts: red boxes denote inclusions of foreign material.

3.2. Sample

In this work, the sample under test is a book cover with rich history, as shown in Fig. 4. Published in Paris, France, a long time ago, it seems to be a children's book. On the cover, the retrospective design clearly reflects a genre of antiquity, and the title (translated from French to English) means “The Little Illustrative Pupil.” The book's width is 18 cm, its height is 27 cm, and its thickness is 3 mm. The book, which belongs to one of Prof. Maldague's grandparents, is safely stored at his parents' home. The main defects in the tested book are surface foxing (caused by fungal growth in the paper), creases (Fig. 4(a)), and tears ($\sim 1.1 \text{ mm} \times 1.1 \text{ mm}$) in the back side (caused by mishandling, as shown in Fig. 4(b)). The primary objective of this study is to identify and assess potential defects and damages in ancient books, thereby making a significant contribution to the preservation, conservation, and promotion of cultural heritage. By employing advanced techniques and methodologies, this research aims to meticulously detect and document any signs of deterioration, including but not limited to structural weaknesses, degradation of materials, fading or illegible text, and other forms of damage. The findings of this study not only facilitate the development of tailored preservation strategies and conservation

protocols but also enhance the understanding, appreciation, and dissemination of our invaluable cultural legacy for generations to come.

4. Methodology

4.1. Image processing methods

Image preprocessing is an essential step in NDT image processing, as it can improve image quality, reduce noise, and enhance contrast. This section reviews some of the most advanced preprocessing techniques, namely, PCA, FFT, and PLSR.

PCA is a method that aims to reduce the dimensionality of the data by transforming the original set of variables into a new set of variables called principal components [5]. It was commonly used for defect detection in metallic/composites materials based on pulsed thermography [47, 48]. PCA works by first calculating the covariance matrix of the original variables. The covariance matrix describes the relationship between the variables and shows how much they vary jointly. If two variables are highly correlated, their covariance is large in magnitude, whereas if they are not correlated, their covariance is zero. The covariance matrix is then decomposed into a set of orthogonal eigenvectors and their corresponding eigenvalues. The eigenvectors represent the directions in the original variable space that explain the largest amount of variation in the data.

The eigenvalues represent the amount of variance explained by each eigenvector. The eigenvectors are sorted in descending order of their corresponding eigenvalues, with the first eigenvector explaining the most important variability and the last eigenvector explaining the least.

FFT is an algorithm used to convert a time-domain signal into its frequency-domain representation [27]. It can be used for extracting the amplitude information of the THz spectrum and determining the moisture content in plants [49, 50]. The principle behind FFT is based on the fact that any stationary signal can be represented as a sum of sinusoidal functions of different frequencies, phases, and amplitudes. The FFT algorithm calculates the frequency components of a signal by dividing it into smaller segments and then applying a complex mathematical formula to each segment. This process converts the time-domain signal into its frequency-domain representation, which provides information about the different frequencies present in the signal and their corresponding amplitudes.

PLSR is a statistical method used to analyze the relationship between two sets of variables where both sets of variables are highly correlated [28]. It has been successfully applied to concrete/pipeline defect detection based on passive thermography [51, 52]. Procedurally, PLSR first calculates the covariance matrix between the input and output variables. The covariance matrix is then decomposed into a set of orthogonal latent variables and their corresponding scores and loadings. The scores represent the projections of the input and output

data onto the latent variables, while the loadings represent the contribution of each input variable to the latent variables. The latent variables are sorted in descending order of their contribution to the output variable, with the first latent variable explaining the most variance in

the output variable and the last latent variable explaining the least. The number of latent variables retained is determined by the amount of variance that must be explained, which is often set to a pre-defined percentage of the total variance.

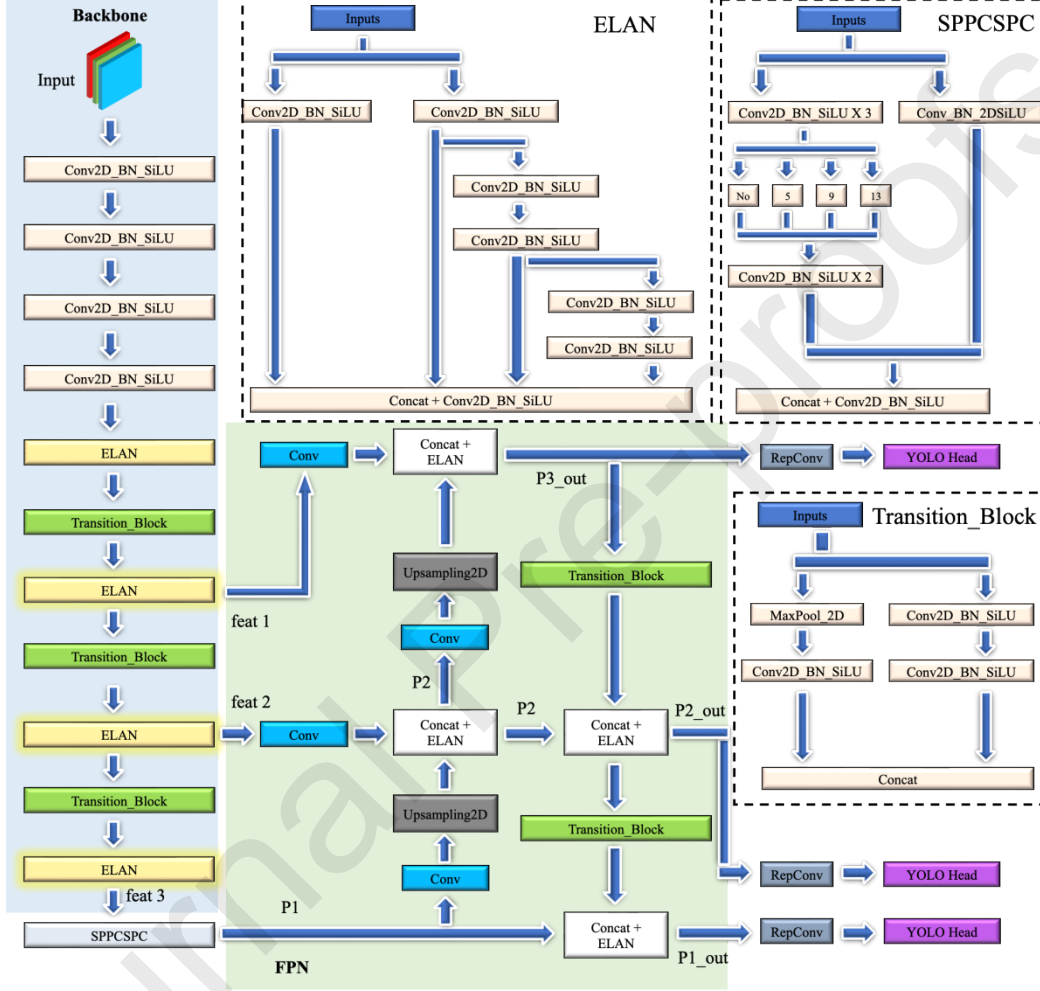


Fig. 5. Network Structure of YOLOv7.

4.2. Automatic defect detection with YOLOv7

The latest version of the YOLO object detection algorithm [29-31], that is, YOLOv7, has gained significant attention recently in the field of non-destructive testing due to its superior performance and fast inference time. In

this work, YOLOv7 is used to detect possible defects and deteriorations of the hand-bound book cover. Additionally, its potential impact on the non-invasive inspection industry is also discussed. The YOLOv7 network is a deep convolutional neural network that consists of three parts, including a backbone network, a feature pyramid

network (FPN), and a head (three output branches), as shown in Fig. 5. There are some special features should be introduced in details [32,33]. For instance, SPPCSPC is a CSPNet with SPP block, where SPP can solve the problem of different input sizes, and CSPNet can improve the expression ability and learning ability of this model. ELAN helps in controlling the longest shortest gradient path which lets a deeper network to learn and converge effectively. Transition_Block module is used for downsampling. RepConv can provide more diversity of gradients for different feature maps.

The backbone network is used to extract features from the input image. It is based on the EfficientNet architecture, which is a family of neural networks designed to achieve state-of-the-art accuracy while minimizing the number of parameters and computations. The backbone generates three feature layers located in the middle layer (feat 1), lower middle layer (feat 2), and bottom layer (feat 3), respectively.

FPN is the enhanced feature extraction network of YOLOv7. Then three feature layers preform feature fusion in FPN in order to combine different feature information of scales. The construction of FPN can be described as follows:

(1) The feature layer of feat 3 preforms feature extraction using SPPCSPC, and generates P1;

(2) P1 preforms convolution and upsampling process. Then it combines with feat 2 processed by convolution, generates P2;

(3) P2 preforms convolution and upsampling process. Then it combines with feat processed by convolution, and generates the first output P3_out;

(4) P3_out preforms Transition_Block and combines with P2, generates the second output P4_out;

(5) P4_out preforms Transition_Block and combines with P1, generates the last output P5_out.

After processed by backbone and FPN, three enhanced feature layers are obtained. Finally, these three feature layers are transferred to the YOLO Head, which is the classifier and regressor depending on the application, for obtaining prediction results.

5. Dataset preparation

As mentioned earlier, deep learning techniques are often confronted by small-sample training data. Therefore, in order to train the YOLOv7 network, the Comsol software and FDTD method are used to constructed a simulated model of the ancient book cover with defects. Here, the CAD and Comsol are used for interactive modeling, of which the resultant modeled book cover is shown in Fig. 6. The thickness of the book cover is 3.1 mm, and the thickness of the pigment layer is 50 μm . In order to resemble as close as possible the real sample, different pigments are chosen and applied to the simulation model based on the real color distribution. Materials properties are shown in Table 1. The length and width of the sample are 27 cm

and 18 cm, respectively.

There are three groups of known defects, located on the front, back, and interior of the book cover. The thickness and radius of the front side defects are 0.02 cm and 0.2 cm (Fig. 6(a)), respectively. The thickness and radius of

the back side circle defects are 0.1 cm and 0.3 cm (Fig. 6(b)), respectively. The thickness and length of the back side square defect is 0.1 cm and 1 cm (Fig. 6(b)), respectively. The thickness and radius of internal defects are 0.1 cm (Fig. 6(b)).

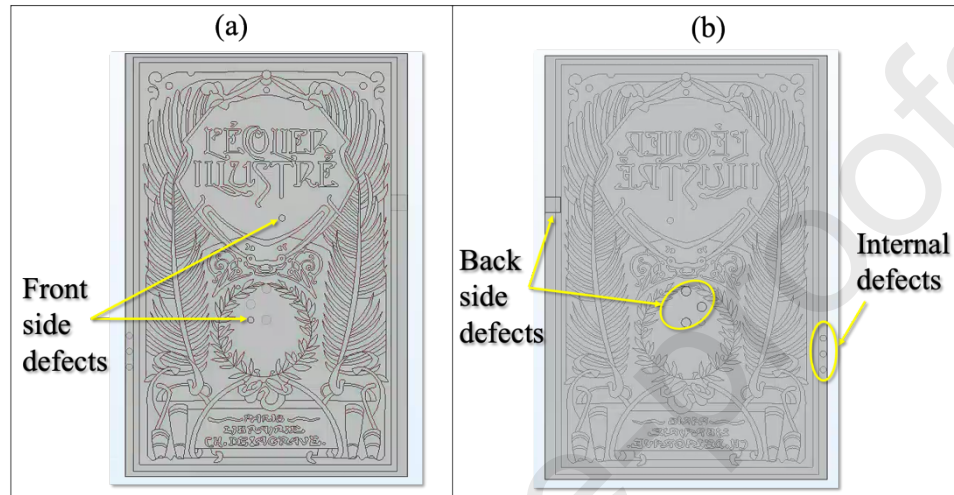


Fig. 6. Simulation model: (a) the front side; (b) the back side.

Table 1

Materials properties of the simulation model.

Materials	Refractive index	Density [kg/m ³]	Heat capacity [J/kg·K]	Thermal Conductivity [W/m·K]
Cadmium red	2.42	4258	1490	2.7
Maple wood	1.5	530	1160	0.15
Chromium oxide green	2.5	4390	1700	2.6
Lemon chrome yellow	1.12	3895	1100	2.1

Ivory black	1.54	2100	720	151
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For IRT, the module that conducts heat transfer in solid is used. The governing equations are given by [34]:

$$\rho C_p \frac{\partial T}{\partial t} + \nabla \cdot \mathbf{q} = Q \quad (1)$$

$$\mathbf{q} = -k \nabla T \quad (2)$$

where ρ denotes density, C_p denotes heat capacity, T denotes temperature, k denotes thermal conductivity, and Q denotes heat source.

The boundary conditions are given by:

$$-\mathbf{n} \cdot \mathbf{q} = q_0 \quad (3)$$

$$q_0 = h(T_{ext} - T) \quad (4)$$

where h denotes convective coefficient, and T_{ext} denotes external temperature. Heat flux with 1.8×10^6 W/m² is applied onto the front surface of the sample for 0.02 s. The convective coefficient is 20 W/(m²×K) applied onto the rest of the faces. The simulation time is 10 s, and the time interval is 0.02 s.

For THz-TDS, the finite-difference time-domain was employed to solve the Maxwell's curl equations. The time-dependent Maxwell's curl equations are arranged in the following form [35]:

$$\frac{\partial \mathbf{E}}{\partial t} = \frac{1}{\varepsilon} \nabla \times \mathbf{H} - \frac{\sigma}{\varepsilon} \mathbf{E} \quad (5)$$

$$\frac{\partial \mathbf{H}}{\partial t} = -\frac{1}{\mu} \nabla \times \mathbf{E} \quad (6)$$

where $\mathbf{E}$ is the electric field, $\mathbf{H}$ is the

magnetic field, ε is the electric permittivity, σ is the electric conductivity, and μ is the magnetic permeability. For a dispersive medium, the electric permittivity ε is frequency-dependent.

In the finite difference time-domain (FDTD) method, the model space is divided into small cubes called Yee cells, with a size δ less than the size of relevant features. The time is divided into small steps Δt , which is much less than the period of the relevant electromagnetic wave. The algorithm is often stable if $\delta \leq \lambda/10$ and $\Delta t \leq \delta/\sqrt{3}$, where δ is the side length of a cubical cell, λ is the wavelength in the material, Δt is the time step, and c is the speed of light in vacuum. In order to remove the reflection from the back boundary, the absorbing boundary condition is imposed. Mur's, Liao's, or perfectly matched layer (PML) absorbing boundary conditions have been chosen since they have an excellent absorbing effect [36-38].

In a 3D Cartesian coordinate system, by substituting the central-difference approximations for space and time derivatives into Maxwell's equations, coupled finite-difference time-stepping expressions arise for the components of the electric field $\mathbf{E}$ and the magnetic field $\mathbf{H}$ [39]. The time-stepping for the field components of a 3D model can be expressed as:

$$\left(1 + \frac{\Delta t \cdot \sigma}{2\varepsilon}\right) (E_x)_{(i+\frac{1}{2}, j, k)}^{n+1} = \left(1 - \frac{\Delta t \cdot \sigma}{2\varepsilon}\right)$$

$$(E_x)_{(i+\frac{1}{2},j,k)}^n + \frac{\Delta t}{\delta \varepsilon} [(H_z)_{(i+\frac{1}{2},j+\frac{1}{2},k)}^{n+\frac{1}{2}} - (H_z)_{(i+\frac{1}{2},j-\frac{1}{2},k)}^{n+\frac{1}{2}} - (H_y)_{(i+\frac{1}{2},j,k+\frac{1}{2})}^{n+\frac{1}{2}} + (H_y)_{(i+\frac{1}{2},j,k-\frac{1}{2})}^{n+\frac{1}{2}}] \quad (7)$$

$$(1 + \frac{\Delta t \cdot \sigma}{2\varepsilon})(E_y)_{(i,j+\frac{1}{2},k)}^{n+1} = (1 - \frac{\Delta t \cdot \sigma}{2\varepsilon})(E_y)_{(i,j+\frac{1}{2},k)}^n + \frac{\Delta t}{\delta \varepsilon} [(H_x)_{(i,j+\frac{1}{2},k+\frac{1}{2})}^{n+\frac{1}{2}} - (H_x)_{(i,j+\frac{1}{2},k-\frac{1}{2})}^{n+\frac{1}{2}} - (H_z)_{(i+\frac{1}{2},j+\frac{1}{2},k)}^{n+\frac{1}{2}} + (H_z)_{(i-\frac{1}{2},j+\frac{1}{2},k)}^{n+\frac{1}{2}}] \quad (8)$$

$$(1 + \frac{\Delta t \cdot \sigma}{2\varepsilon})(E_z)_{(i,j,k+\frac{1}{2})}^{n+1} = (1 - \frac{\Delta t \cdot \sigma}{2\varepsilon})(E_z)_{(i,j,k+\frac{1}{2})}^n + \frac{\Delta t}{\delta \varepsilon} [(H_y)_{(i+\frac{1}{2},j,k+\frac{1}{2})}^{n+\frac{1}{2}} - (H_y)_{(i-\frac{1}{2},j,k+\frac{1}{2})}^{n+\frac{1}{2}} - (H_x)_{(i,j+\frac{1}{2},k+\frac{1}{2})}^{n+\frac{1}{2}} + (H_x)_{(i,j-\frac{1}{2},k+\frac{1}{2})}^{n+\frac{1}{2}}] \quad (9)$$

$$(1 + \frac{\Delta t \cdot \sigma}{2\mu})(H_x)_{(i,j+\frac{1}{2},k+\frac{1}{2})}^{n+1} = (1 - \frac{\Delta t \cdot \sigma}{2\mu})(H_x)_{(i,j+\frac{1}{2},k+\frac{1}{2})}^n - \frac{\Delta t}{\delta \mu} [(E_z)_{(i,j+1,k+\frac{1}{2})}^n - (E_z)_{(i,j,k+\frac{1}{2})}^n - (E_y)_{(i,j+\frac{1}{2},k+1)}^n + (E_y)_{(i,j+\frac{1}{2},k)}^n] \quad (10)$$

$$(1 + \frac{\Delta t \cdot \sigma}{2\mu})(H_y)_{(i+\frac{1}{2},j,k+\frac{1}{2})}^{n+1} = (1 - \frac{\Delta t \cdot \sigma}{2\mu})(H_y)_{(i+\frac{1}{2},j,k+\frac{1}{2})}^n - \frac{\Delta t}{\delta \mu} [(E_x)_{(i+\frac{1}{2},j,k+1)}^n - (E_x)_{(i+\frac{1}{2},j,k)}^n - (E_z)_{(i,j,k+\frac{1}{2})}^n + (E_z)_{(i,j+1,k+\frac{1}{2})}^n] \quad (11)$$

$$(H_x)_{(i+\frac{1}{2},j,k+\frac{1}{2})}^{n-\frac{1}{2}} - \frac{\Delta t}{\delta \mu} [(E_x)_{(i+\frac{1}{2},j,k+1)}^n - (E_x)_{(i+\frac{1}{2},j,k)}^n - (E_z)_{(i,j,k+\frac{1}{2})}^n + (E_z)_{(i,j+1,k+\frac{1}{2})}^n] \quad (12)$$

$$(1 + \frac{\Delta t \cdot \sigma}{2\mu})(H_z)_{(i+\frac{1}{2},j+\frac{1}{2},k)}^{n-\frac{1}{2}} = (1 - \frac{\Delta t \cdot \sigma}{2\mu})(H_z)_{(i+\frac{1}{2},j+\frac{1}{2},k)}^{n-\frac{1}{2}} - \frac{\Delta t}{\delta \mu} [(E_y)_{(i+1,j+\frac{1}{2},k)}^n - (E_y)_{(i,j+\frac{1}{2},k)}^n - (E_x)_{(i+\frac{1}{2},j+1,k)}^n + (E_x)_{(i+\frac{1}{2},j,k)}^n] \quad (12)$$

where i, j , and k represent the nodes of the Yee cells, and n represents the calculated time step. Equations (7)-(9) represent the electric field components, which are located on the three edges at each Yee cell. Equations (10)-(12) represent the magnetic field components, which are located in the middle of the three surfaces. In addition to the one-half spatial-cell displacement between E and H , there is also one-half time-cell displacement. In this work, the simulation time is 60 ps. The plane wave as light source is injected into the wood, with a frequency of 1 THz, a pulse length of 0.5 ps, an offset of 5 ps, and a bandwidth of 1.75 THz.

Fig. 7 shows examples of the simulation results for IRT and THz-TDS. Results are approximately identical to experimental results, demonstrating the validity of the simulation. The texture of the book cover can be observed clearly, and defects can be detected. There are 2796 infrared images and 600 THz

images generated through simulation in this work. To obtain sufficient train datasets, defects size and depths are changed for each simulation. Generated simulation results of IRT and THz-TDS are along with the training – validation – testing division (75% - 12.5% - 12.5%).

6. Result and discussion

6.1. Experimental result

Fig. 8 shows original images of IRT at different times during the exposure process. When time $t = 0.04$ s, surface cracks, and internal holes are obvious based on the temperature difference between the normal and defect areas.

When $t = 0.14$ s, several defects become invisible, especially on the left side of the book cover. When $t = 2$ s, the texture of the book cover becomes clear. When $t = 4$ s, the texture of the book cover becomes blurred, and surface cracks and internal holes cannot be observed. However, there are some obvious light spots on the left side of the book cover, as well as near the center of the cover, which denote deeper defects.

Fig. 9 shows original images of THz-TDS at different times. When $t = 34.77$ ps, there are many white spots on the book cover, which denote internal defects. In addition, there is an obvious crack on the top-right corner of the book cover, as shown in Fig. 9(a). When $t = 36.20$ ps, in addition to some spots being visible, a distinct crack can be seen

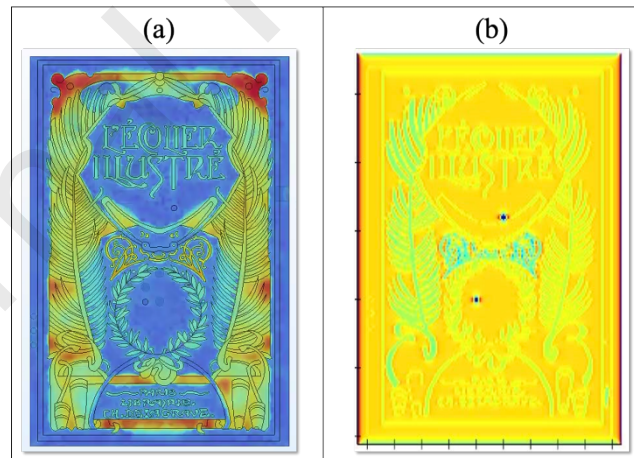


Fig. 7. Simulation results for training: (a) IRT; (b) THz-TDS.

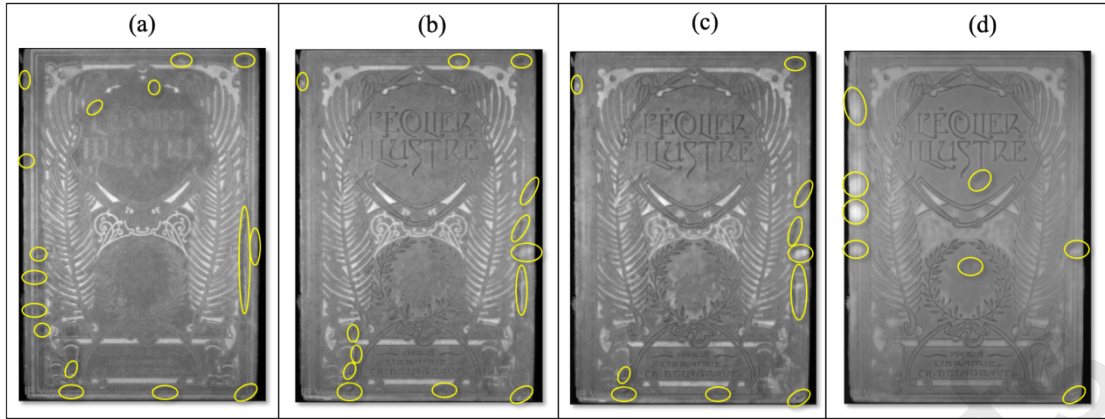


Fig. 8. Original images of IRT at different times (t): (a) 0.04 s; (b) 0.14 s; (c) 2 s; (d) 4 s. Yellow circles denote defects.

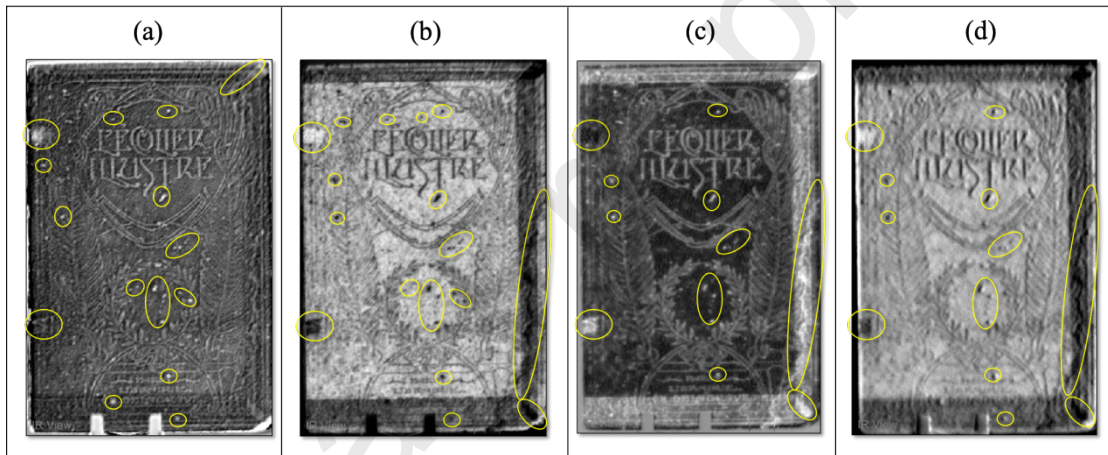


Fig. 9. Original images of THz-TDS at different times: (a) 34.77 ps; (b) 36.20 ps; (c) 37.26 ps; (d) 75.02 ps. Yellow circles denote defects.

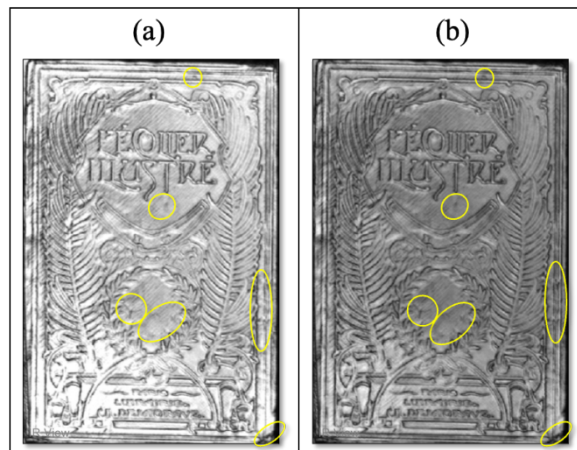


Fig. 10. Peak-to-peak images from ACU at different gains: (a) 53 dB; (b) 49 dB.

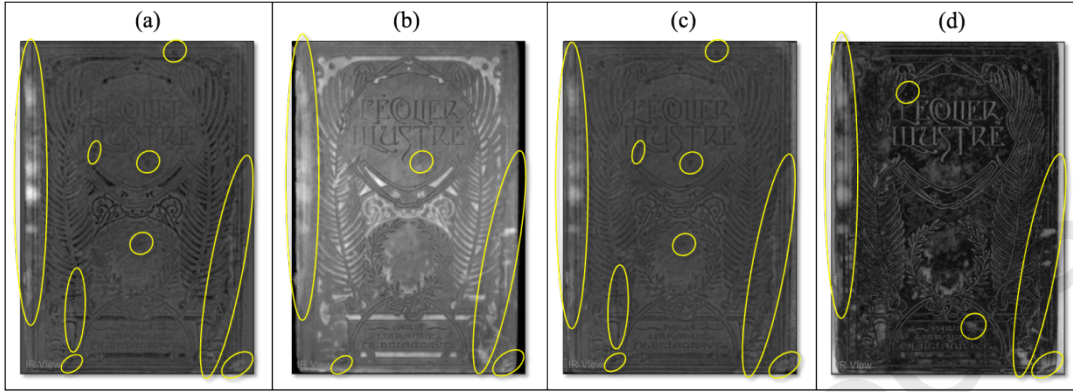


Fig. 11. Image processing for IRT: (a) PCA; (b) FFT amplitude; (c) FFT phase; (d) PLSR.

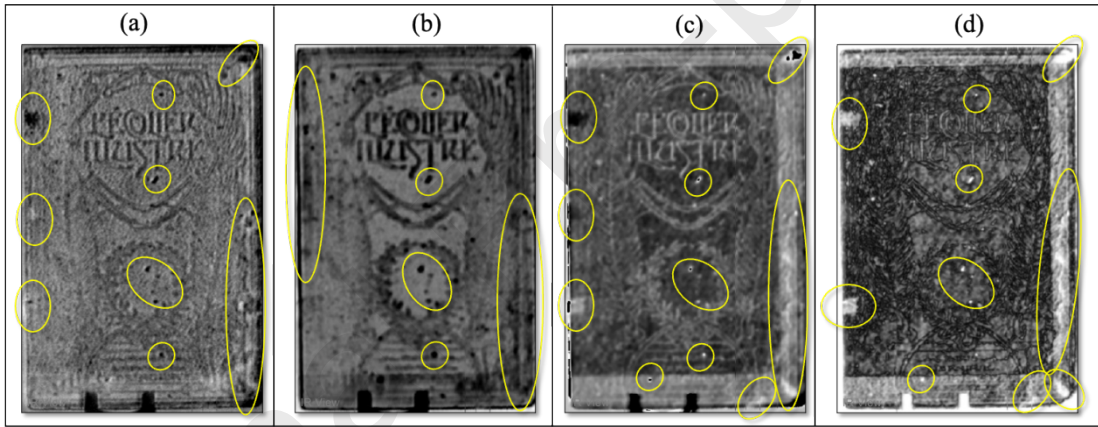


Fig. 12. Image processing for THz-TDS: (a) PCA; (b) FFT amplitude; (c) FFT phase; (d) PLSR.

on the right side of the book cover. When $t = 37.26$ ps, the color of this crack changes from black to white and becomes more obvious. When $t = 75.02$ ps (time is located in the second pulse-echo), defects can also be detected. Furthermore, the THz-TDS technique can detect the defects on the back side of the book cover in Fig. 4(b) by inspecting the left side of the book cover in Fig. 9.

Fig. 10 shows peak-to-peak results from ACU at different gains. Both results are similar, except for some differences in brightness. The texture of the book cover is obviously based on the ACU technique. There are some defects in the middle of the book cover. In addition, the crack on the right side of the book cover can be detected clearly.

Summarizing the observations made thus far with three different non-invasive inspection techniques, it is possible to conclude that the IRT technique is suitable for detecting surface defects, whereas it is hard to detect deep defects. ACU technique can detect internal defects, but it is not sensitive to surface defects. The THz-TDS technique has the highest resolution along the deep

direction. It means that the THz-TDS technique can detect the most internal defects and recover the profile of internal defects. However, the THz-TDS technique has relatively little spatial resolution, limited by the displacement distance of the scanning platform. Therefore, it is hard to recover the surface texture of the book cover.

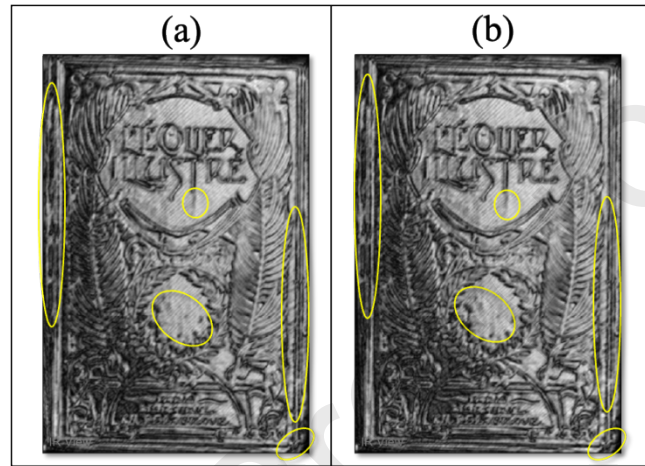


Fig. 13. Image processing for ACU: (a) FFT amplitude at 49 dB; (b) FFT amplitude at 53 dB.

6.2. Image processing

Image processing involves manipulating and analyzing digital images to extract useful information or enhance the quality of the image. In this section, different image processing methods were applied to the original images of IRT, THz-TDS, and ACU. It is noted that the authors only use effective images in this paper, because not every method can be effectively applied to different non-invasive inspection techniques.

Fig. 11 shows the image processing

results for IRT. Defects on left side of the book cover can be detected in every image. Furthermore, there is a long crack at the right side of the book cover. Images from PCA and FFT phases lead to similar detection results. The PLSR can detect defects which are not detectable from other images.

Fig. 12 shows the image processing results for THz-TDS. It is possible to find that the processed images become blurred, especially for the texture of the book cover, while the defect information remains. For the PCA image and FFT amplitude image, defects located at both sides of the book cover are not clear

enough. In the PLSR image it contains a high level of noise, but the defect information remains obvious. In summary, comparing all processed images, the FFT phase image allows detection of defects in the most thorough manner.

Fig. 13 shows the image processing results for ACU at different gains. For ACU images, only FFT is used. Because other image processing method are not only ineffective, but also destroy the original images. FFT amplitudes at 49 dB

and 53 dB give similar detection results, especially at the left side of the book cover, which was not observed in the original images (Fig. 10). However, detection results based on the ACU technique are far inferior to IRT and THz-TDS, although the ACU technique can detect several holes in the middle of the book cover which are not detected by IRT. In other words, ACU technique loses many defect information, especially for surface defects.

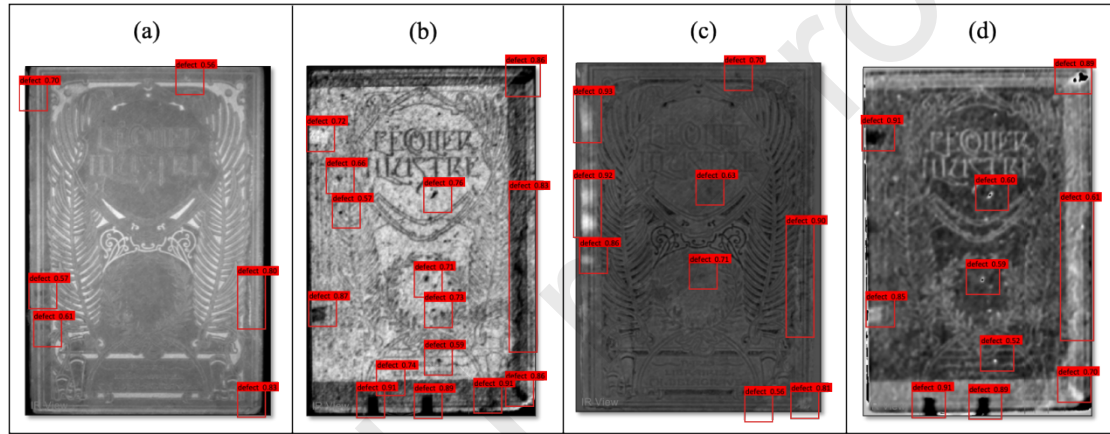


Fig. 14. Automatic defect detection: (a) original IRT image; (b) original THz-TDS image; (c) PCA image for IRT; (d) FFT phase image for THz-TDS.

6.3. Automatic defect detection

Automatic defect detection technology plays a crucial role in preserving cultural heritage, particularly in ensuring the longevity and integrity of historical artifacts and structures [40-43]. The importance of this technology lies in its ability to automatically identify and assess defects in cultural heritage without human intervention, thereby significantly reducing the risk of human error and subjectivity in the preservation process.

The YOLOv7 algorithm is particularly useful for detecting objects in complex environments such as those encountered in IRT and THz-TDS [44-46]. ACU was excluded to its poor defect detection in the previous part of the case study. Nevertheless, IRT and THz-TDS techniques often generate noisy and low-resolution images, making it difficult to identify objects accurately. To address this issue, the introduction of YOLOv7 is warranted, as it can effectively address these challenges through the utilization of a multi-scale feature extraction

approach and the integration of information derived from diverse layers of the neural network. By leveraging this advanced methodology, YOLOv7 can proficiently analyze objects across a range of scales and amalgamate complementary features extracted from disparate network layers. Thus, this cutting-edge framework is capable of circumventing the limitations of earlier algorithms, providing highly precise and robust object detection capabilities. The incorporation of such sophisticated techniques in YOLOv7 marks a significant advancement in the field of object detection, surpassing its predecessors in terms of accuracy and reliability.

As shown in Fig. 14(a) and (b), in the original image of IRT, defects located at the edges of the book cover can be detected effectively. In contrast, defects located near the center of the book cover cannot be detected. For the original image of THz-TDS, it is obvious to find that almost all black spots are identified as defects. Furthermore, the clamp for the book cover is also identified as defects.

As shown in Fig. 14(c) and (d), for the PCA image of IRT, the defects near the center of the book cover can now be detected. In addition, defects located on the left side of the book cover are also detected. For the FFT phase image of THz-TDS, main defects can be detected, although there are some defects that are ignored. The experimental results illustrate that simulation datasets can be used for training YOLOv7 network. Furthermore, the trained model can be used to detect both original image and processed image automatically.

7. Conclusion

This work is concerned with the application of non-invasive inspection methods in the detection of defects in cultural heritage, which has gained significant attention in the recent years. Whereas the test subject is an ancient book cover, three distinct non-invasive inspection techniques—infrared thermography (IRT), terahertz time-domain spectroscopy (THz-TDS), and air-coupled ultrasound (ACU)—are considered to acquire the raw images needed for the detection of defects. In order to extract useful information and reduce image noise, three advanced image processing algorithms—principal component analysis (PCA), fast Fourier transform (FFT), and partial least squares regression (PLSR)—are employed to analyze the images collected by these non-invasive inspection techniques. Last but not least, to automate the process of defect detection, the state-of-the-art YOLOv7 deep learning algorithm is used. This object detection algorithm employs a form of convolutional neural network to detect and localize objects in an image. It is capable of achieving high accuracy and fast processing times, making it a suitable choice for defect detection for ancient books. To collect a sufficiently rich dataset for training, finite element methods are used to generate simulated data. Experimental results show excellent detection effect in original image and processed image based on YOLOv7 algorithm.

In summary, our study showcases

the potential of using a combination of advanced non-invasive inspection methods and image processing techniques for the detection of defects in ancient books. Our findings demonstrate that the integration of PCA, FFT, and PLSR algorithms, along with the YOLOv7 algorithm, can lead to an efficient and accurate method for defect detection in ancient books, thus aiding in their preservation and transfer to future generations.

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References

- [1] M. Attas, E. Cloutis, C. Collins, et al. Near-infrared spectroscopic imaging in art conservation: investigation of drawing constituents, *J. Cult. Herit.* 4 (2003) 127-136.
- [2] J. Hu, H. Zhang, S. Sfarra, et al. Novel infrared-terahertz fusion 3D non-invasive imaging of plant fibre-reinforced polymer composites, *Compos. Sci. Technol.* 226 (2022) 109526.
- [3] H. Zhang, P. Verberne, S.A. Meguid, et al. Autonomous high resolution inspection of kiss-bonds skins of carbon nanotube reinforced nanocomposites using novel dynamic line-scan thermography approach, *Compos. Sci. Technol.* 192 (2020) 108111.
- [4] H. Zhang, L. Yu, U. Hassler, et al. An experimental and analytical study of micro-laser line thermography on micro-sized flaws in stitched carbon fiber reinforced polymer composites, *Compos. Sci. Technol.* 126 (2016) 17-26.
- [5] H. Zhang, F. Robitaille, C.U. Grosse, et al. Optical excitation thermography for twill/plain weaves and stitched fabric dry carbon fibre preform inspection, *Compos. Part A-Appl. S.* 107 (2018) 282-293.
- [6] M. Tortora, S. Sfarra, M. Chiarini, et al. Non-destructive and micro-invasive testing techniques for characterizing materials, structures and restoration problems in mural paintings, *Appl. Surf. Sci.* 387 (2016) 971-985.
- [7] H. Zhang, S. Sfarra, K. Saluja, et al. Non-destructive Investigation of Paintings on Canvas by Continuous Wave Terahertz Imaging and Flash Thermography, *J. Nondestruct. Eval.* 36 (2017) 34.
- [8] Y. Liu, F. Wang, K. Liu, et al. Deep convolutional autoencoder

- thermography for artwork defect detection, *Quant. Infr. Therm. J.* 2023. DOI: 10.1080/17686733.2023.2225246.
- [9] K. Liu, K.L. Huang, S. Sfarra, et al. Factor analysis thermography for defect detection of panel paintings, *Quant. Infr. Therm. J.* 20 (2023) 25-37.
- [10] F. Mercuri, C. Cicero, N. Orazi, S. et al. Infrared thermography Applied to the study of cultural heritage, *Int. J. Thermophys.* 36 (2015) 1189-1194.
- [11] M. Tortora, S. Sfarra, C. Casieri. NMR relaxometry and IR thermography to study ancient cotton paper bookbinding, *Appl. Sci-Basel.* 9 (2019) 3406.
- [12] F. Aymerich, S. Meili. Ultrasonic evaluation of matrix damage in impacted composite laminates, *Compos. Part B-Eng.* 31 (2000) 1-6.
- [13] T.H. Gan, D.A. Hutchins, D.R. Billson, D.W. Schindel. The use of broadband acoustic transducers and pulse-compression techniques for air-coupled ultrasonic imaging, *Ultrasonics.* 39 (2001) 181-194.
- [14] H. Zhang, S. Sfarra, A. Osman, et al. Using through-transmission mid-wave infrared vision and air-coupled ultrasound for artwork inspection: a case study on mock-ups of Portrait of the Painter's Mother, *Insight.* 62 (2020) 123-128.
- [15] H. Fernandes, J. Summa, J. Daudre, et al. Characterization of ancient marquetry using different non-destructive testing techniques, *Appl. Sci-Basel.* 11 (2021) 7979.
- [16] H.A. Gebbie, N. Stone, F.D. Findlay. A Stimulated Emission Source at 0.34 Millimetre Wave-length, *Nature.* 202 (1964) 685-685.
- [17] P. Zhu, H. Zhang, E. Pivarčiová, et al. Characterization of water content and inspection of delamination in spruce, oak and meranti woods after pyrolysis processing using a new terahertz time-domain spectroscopy method, *NDT & E Int.* 139 (2023) 102938.
- [18] H. Zhang, S. Sfarra, A. Osman, et al. An Infrared-Induced Terahertz Imaging Modality for Foreign Object Detection in a Lightweight Honeycomb Composite Structure, *IEEE T. Ind. Inform.* 14 (2018) 5629-5636.
- [19] Z.W. Zhang, Y. Zhang, G.Z. Zhao, et al. Terahertz time-domain spectroscopy for explosive imaging, *Optik.* 118 (2017) 325-329.
- [20] P. Zhu, H. Zhang, C. Santulli, et al. Contactless and nondestructive evaluation of residual stress distribution in modified and pure HDPE materials using a novel terahertz method and line-scan thermographic technique, *Compos. Part A-Appl.* 183 (2024) 108220.
- [21] M. Picollo, K. Fukunaga, J. Labaune. Obtaining noninvasive stratigraphic details of panel paintings using terahertz time domain spectroscopy imaging system, *J. Cult. Herit.* 16 (2015) 73-80.

- [22] E.S. Reyes-Reyes, R. Carriles-Jaimes, E. D'Angelo, et al. Terahertz time-domain imaging for the examination of gilded wooded artifacts, *Sci. Rep.* 14 (2024) 6261.
- [23] A. Artesani, R. Lamuraglia, F. Menegazzo, et al. Terahertz time spectroscopy in reflection configuration for inorganic and mineral pigment identification, *Appl. Spectrosc.* 77 (2023) 74-87.
- [24] K. Fukunaga. Nondestructive evaluation of lined paintings by THz pulsed time-domain imaging, *Heritage* 6 (2023) 3448-3460.
- [25] C.F.J. Kuo, C.P. Tung, W.H. Weng. Applying the support vector machine with optimal parameter design into an automatic inspection system for classifying micro-defects on surfaces of light-emitting diode chips, *J. Intell. Manuf.* 30 (2019) 727-741.
- [26] X.Y. Yang, Y.F. Zhang, W. Lv, et al. Image recognition of wind turbine blade damage based on a deep learning model with transfer learning and an ensemble learning classifier, *Renew. Energ.* 163 (2021) 386-397.
- [27] P. Zhu, H. Zhang, S. Sfarra, et al. Enhancing resistance to low-velocity impact of electrospun-manufactured interlayer-strengthened CFRP by using infrared thermography, *NDT & E Int.* 144 (2024) 103083.
- [28] F. Lopez, C.I. Castanedo, V.D. Nicolau, et al. Optimization of pulsed thermography inspection by partial least-squares regression, *NDT & E Int.* 66 (2014) 128-138.
- [29] J. Chen, B. Ma, C. Ji, et al. Apple inflorescence recognition of phenology stage in complex background based on improved YOLOv7, *Comput. Electron. Agric.* 211 (2023) 108048.
- [30] C. Yi, J. Liu, T. Huang, et al. An efficient method of pavement distress detection based on improved YOLOv7, *Meas. Sci. Technol.* 34 (2023) 115402.
- [31] B. Zhu, G. Xiao, Y. Zhang, et al. Multi-classification recognition and quantitative characterization of surface defects in belt grinding based on YOLOv7, *Measurement* 216 (2023) 112937.
- [32] Y. Zhang, Y.P. Sun, Z. Wang, et al. Yolov7-RAR for urban vehicle detection, *Sensors* 23 (2023) 1801.
- [33] Z. Huang, J. Wang, X. Fu, et al. DC-SPP-YOLO: Dense connection and spatial pyramid pooling based YOLO for object detection, *Inf. Sci.* 522 (2020) 241-258.
- [34] P. Zhu, R. Wang, S. Sfarra, et al. A novel force-temperature model for evaluating internal forces in CFRP by means of infrared thermography, *NDT & E Int.* 143 (2024) 103066.
- [35] P.A. Tirkas, C.A. Balanis, M.P. Purchine, et al. Finite-difference time-domain method for electromagnetic radiation, interference, and interaction with complex structures, *IEEE Trans. Electromagn. C.* 35 (1993) 192-203.
- [36] J.P. Berenger. A perfectly matched layer for the absorption of

- electromagnetic waves, *J. Comput. Phys.* 114 (1994) 185-200.
- [37] G. Mur. Absorbing boundary conditions for the finite difference approximation of the time-domain electromagnetic field equations, *IEEE Trans. Electromagn. C.* 4 (1981) 377-382.
- [38] Z.P. Liao, H.L. Wong, B.P. Yang, et al. A transmitting boundary for transient wave analysis, *Sci. Sin.* 27 (1984) 1063-1076.
- [39] A. Taflove, K.R. Umashankar. The finite-difference time-domain method for numerical modeling of electromagnetic wave interactions, *Electromagnetics* 10 (1990) 105-126.
- [40] L.E. Mansuri, D.A. Patel. Artificial intelligence-based automatic visual inspection system for built heritage. *Smart Sustain, Built Environ.* 11 (2022) 622-646.
- [41] I. Garrido, J. Erazo-Aux, S. Lagüela, et al. Introduction of deep learning in thermographic monitoring of cultural heritage and improvement by automatic thermogram pre-processing algorithms, *Sensors* 21 (2021) 750.
- [42] J.A.M. Garcia, E. Yahaghi, A. Movafeghi. Improvement of the digital radiographic images of old paintings on wooden support through the anisotropic diffusion method, *J. Cult. Herit.* 49 (2021) 115-122.
- [43] S. Paoloni, N. Orazi, U. Zammit, et al. A note on the early thermographic approaches for the investigation of the Cultural Heritage, *Quant. Infr. Therm. J.* 2023. DOI: 10.1080/17686733.2023.2243575.
- [44] F. Xu, X. Huang, Q. Wu, et al. YOLO-MSFG: Toward real-time detection of concealed objects in passive terahertz images, *IEEE Sens. J.* 22 (2022) 520-534.
- [45] D.G. Lema, O.D. Pedrayes, R. Usamentiaga, et al. Automated detection of subsurface defects using active thermography and deep learning object detectors, *IEEE Trans. Instrum. Meas.* 71 (2022) 4503213.
- [46] T. Cheng, L. Song, Y. Ge, et al. YOLO-World: Real-Time open-vocabulary object detection, *arXiv preprint arXiv: 2401.17270*, 2024.
- [47] P. Zhu, H. Zhang, F. Robitaille, et al. Terahertz time-domain spectroscopy for the inspection of dry fibre preforms, *NDT & E Int.* 145 (2024) 103133.
- [48] N. Rajic. Principal component thermography for flaw contrast enhancement and flaw depth characterization in composite structures, *Compos. Struct.* 58 (2002) 521-528.
- [49] M. Kashyap, J. Torniainen, K. Bertling, et al. Coherent terahertz laser feedback interferometry for hydration sensing in leaves, *Opt. Express* 31 (2023) 23877-23888.
- [50] W. Nsengiyumava, S. Zhong, L. Zheng, et al. Sensing and nondestructive testing applications of terahertz spectroscopy and imaging systems: State-of-the-art and state-of-

the-practice, IEEE Trans. Instrum. Meas. 72 (2023) 4507483.

[51]M.P.V. de Souza, F. López, X. Maldague. Corrosion under insulation mitigation by passive multivariate thermography, Quant. Infrared Thermogr. J. 2024. DOI: 10.1080/17686733.2024.2305917.

[52]S. Pozzer, Z. Omid, A.E. Refai, et al. Passive infrared thermography for subsurface delamination detection in concrete infrastructure: Capabilities, Constr. Build. Mater. 419 (2024) 135542.

Highlights

- 1) Three distinct non-invasive inspection methods are used, including infrared thermography, terahertz time-domain spectroscopy, and air-coupled ultrasound.
- 2) To improve the image quality and extract the useful defect information, advanced image processing methods are performed.
- 3) YOLOv7, as an automatic defect detection deep learning network, is applied.
- 4) To obtain a sufficient dataset to train the network, the finite element analysis and finite-difference time-domain method are introduced.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:



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Non-invasive inspection for a hand-bound book of the 19th century: numerical simulations and experimental analysis of infrared, terahertz, and ultrasonic methods

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