Research Article

Metal Detection of Wood Based on Thermal Signal Reconstruction Algorithm

Hong Zhang,1,2 Ruizhen Yang,3 Wenhui Chen,1,2 and Ruikun Wu1,2

1Key Laboratory of Non-destructive Testing Technology (Fujian Polytechnic Normal University), Fujian Province University, China
2School of Electronic and Mechanical Engineering, Fujian Polytechnic Normal University, China
3College of Civil Engineering, Changsha University, China

Correspondence should be addressed to Hong Zhang; zhhgw@hotmail.com

Received 17July 2021; Accepted 8November 2021; Published 28November 2021

Academic Editor: Eduard Llobet

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In this paper, eddy current thermography is used to detect metal in wood materials, and thermal signal reconstruction (TSR) algorithm has been proposed to solve the problem of low resolution of metal detection. The basic principle of current nondestructive testing technologies for wood materials has been briefly reviewed, and the advantages and disadvantages have been analyzed. TSR algorithm can significantly enhance the contrast ratio between metal and surrounding areas, different quantities of metal can be effectively identified, and metal positions can be accurately realized. The experimental results show that the proposed eddy current thermography technology can quickly detect metal in wood materials and improve the efficiency and accuracy. The size and quantity of metal can be intuitively observed through thermal images.

1. Introduction

With the rapid development of modern industry, China’s wood processing industry has developed rapidly. In 2021, the global wood market will reach 41.273 billion US dollars [1]. The wood trading market is an important part of the commodity trading market, which plays an important role in promoting the trading and circulation of wood products and stimulating the local economy [2]. In the process of wood production, there are metal materials in wood, which have a negative impact on the use and commercial value of wood. The existence of metal in wood usually reduces the strength of wood and also affects the appearance and processing process of wood. Therefore, the detection of metal in wood can improve the use safety and maximize the economic benefits.

At present, nondestructive testing of wood materials mainly includes defect detection and mechanical property measurement [3]. The basic methods of nondestructive testing mainly include stress wave method, mechanical stress deformation method, vibration method, microdrilling resistance method, ray method, and radar wave method. According to different wood materials, there are different detection methods, and the metal detection technology for ancient building wood materials is most widely used by stress wave method [4]. The general principle of stress wave for metal detection is that when impact force is applied to wood material, stress waves will be generated inside wood and propagate around. Sensors at both ends are used to receive signals of stress waves. The time difference between two points is calculated in a timer, and then, the propagation speed change of stress waves is obtained to judge the condition of metal inside wood materials. Compared with CT, X-ray, and the like, stress wave in wood materials has the advantages of lower cost, safety and reliability, harmlessness to human body, unaffected by tested materials and sizes, suitability for various environments, and can accurately judge whether there are metals, cavities, and wood knots in wood materials. However, the propagation of stress wave in wood is a complex dynamic process, which is affected by many factors, including
the following aspects: the properties of wood, microstructure of wood, water content of wood, defects of wood, and wood morphology [5]. Additional, stress wave systems can only be used for qualitative testing. Additional NDT methods are required to obtain quantitative results in regard to the size and depth of metal.

This paper proposes eddy current thermography for wood metal detection. Eddy current shielded by vacuum magnetic can effectively improve the sensitivity of ferromagnetic metal. It is a nondestructive and noncontact detection technology based on eddy current effect. It has the characteristics of high linearity, high resolution, fast response, simple structure, and static and dynamic measurement [6]. Eddy current excited thermography technology employed the different thermal radiation physical characteristics of structures or materials to detect various defects and damages on the surface or inside of materials. The obtained thermal images have the disadvantages of fuzzy edge, noise interference, and low resolution. In order to improve the accuracy, efficiency, and resolution of defect detection, different feature extraction algorithms have been used to extract defect information. Xingwang et al. carried out wavelet transform on thermal image sequence, and image fusion algorithm based on pixel level and feature level has been used to process thermal image sequence [7].

The test results of aluminum alloy samples show that the image fusion algorithm can effectively reduce the adverse effects of uneven heating and background noise on defect recognition. To enhance cracks characteristics in the original IR images, Peng et al. applied eddy current pulsed thermography (ECPT) for motor winding defects detection with fast Fourier transform (FFT) and principal component analysis (PCA) by eliminating the nonuniform heating effect [8]. L-shaped ferrite magnetic open sensing structure was proposed for fatigue crack inspection on metallic materials with anomalistic geometry. The modified eddy current pulsed thermography system has better performance in omnidirectional microfatigue crack detection. He et al. discussed the applications of deep learning applied infrared imaging-based machine vision. The principle, cameras, and thermal data of infrared imaging-based machine vision have been reviewed [9].

He et al. used fast Fourier transform (FFT) to process phase-locked thermal imaging data, and its calculation speed is faster than discrete Fourier transform and can observe defect information in frequency domain [10]. The fitting function relationship is used to realize the quantitative recognition of defects in infrared thermal wave detection. Numerical calculation method is used to provide samples for training neural network, which proves the feasibility of the method. Rajic employed principal component analysis (PCA) method to decompose the thermal image sequence into a group of orthogonal statistical patterns by singular value decomposition [11]. PCA is used to reduce redundancy, remove noise, and improve the accuracy of detection. Liang et al. used wavelet transform and PCA to detect the impact defects of composite materials [12]. Sripragash and Sundaresan used thermal signal reconstruction (TSR) to detect the defect depth. Temporal and spatial resolutions of thermal image sequence have been improved [13]. Hyvarinen and Oja employed independent component analysis (ICA) method that is used to extract independent components in thermal image sequence to remove data redundancy and obtain high-order statistical characteristics [14]. Swita and Suszyński used kd-tree algorithm to cluster infrared thermal image sequence to extract depth information and reduce the amount of data [15]. Maldague and Marinetti proposed pulse phase infrared thermography (PPT) algorithm, which transforms the time and space information into the frequency domain through Fourier transform to obtain the phase and amplitude information. The defect information can be extracted through the difference of the phase and amplitude between the defect and nondefect regions [16]. A hybrid multidimensional feature fusion structure of spatial and temporal segmentation model was proposed by Hu et al. for defect detection with thermography. The semantic information can be captured easily. He et al. made a profound study infrared machine vision and infrared thermography with deep learning [17]. Theoretical research and case study method are used in this review paper.

In order to improve the detection accuracy and metal resolution, this paper employed thermal signal reconstruction algorithm to detect metal in wood. The metal materials in wood are measured with eddy current thermography, and the infrared thermal images are analyzed by the proposed TSR algorithm. Compared with the stress wave method, it has advantage of nondestructive testing. Furthermore, the position, size, and number of metal materials are detected.

The rest of paper is organized as follows: Firstly, the proposed method is introduced in Section 2. The experimental set-up is described, and feature extraction and optimization are introduced in Section 3. Then, wood with different metal is characterized. It can prove the accuracy and efficiency of eddy current thermal imaging method in the detection of wood materials. Finally, conclusions are outlined in Section 4.

2. Methods and Image Processing

2.1. Principle of Eddy Current Thermography. As shown in Figure 1, the measurement device is mainly composed of an excitation system, an excitation coil, IR camera, a cooling system, an excitation system, sample under test, and a PC. Thermal information of eddy current and materials under test is obtained by IR camera. Different types of information can be obtained according to different analysis methods, and corresponding defect information can be obtained by analyzing these information. Eddy current thermography is based on electromagnetic induction, which involves many physical processes such as Joule heating, heat conduction, and infrared radiation. When the excitation coil carrying high-frequency alternating current is close to the conductor to be tested, under the action of the magnetic field of the coil, eddy current will be generated in the place where there are metal bodies or defects in the conductor to be tested, and eddy current will generate heat in the place where there are foreign bodies or defects in the sample under test, causing temperature changes on the surface of the material and from the inside through heat conduction. The information of foreign bodies or defects in materials can be obtained by graphic analysis and processing collected by IR camera.
The eddy current thermography detection technology can evaluate the metal in the reflection mode and the penetration mode, respectively [18]. With eddy current thermography detection technology in penetration mode can easily detect the surface fracture structure caused by metal. But there are the following disadvantages: (1) Due to the shape of the coil, it will bring uneven heating effect; (2) As time increases, lateral blurring will occur; (3) Periodic wood structure causes thermal abnormalities. Therefore, eddy current thermography in the reflection mode has been employed for the metal evaluation in wood.

2.1.1. Electromagnetic Induction Heating. When the excitation coil passes through alternating current with frequency $f$, induced eddy current with the same frequency is generated inside the tested material according to the law of electromagnetic induction. Time-varying equation of eddy current excitation in eddy current pulse thermal imaging is as follows:

$$J_e + \nabla \times \left( \frac{1}{\mu} \nabla \times A \right) - \frac{\sigma}{\sqrt{\mu \epsilon}} \times (\nabla \times A) = \sigma \frac{V_{\text{loop}}}{2\pi r_d} + J_s. \quad (1)$$

Among them, $\mu$ is the magnetic permeability of the measured material, and $\epsilon$ is the dielectric constant and eddy current density of the measured material:

$$J_e = \frac{\partial A}{\partial t}, \quad (2)$$

where $J_e$ is the current density of the excitation coil, $V_{\text{loop}}$ is the loop potential, and $r_d$ is the loop radius, which is the conductivity of the material. $A$ is the magnetic vector potential instead of the magnetic induction intensity $B$ to satisfy:

$$B = \nabla \times A. \quad (3)$$

Due to the resistance inside the material, eddy current is converted from electric energy to heat energy inside the material. According to Joule’s law, the generated thermal power $P_w$ is proportional to the eddy current density $J_e$ and the electric field strength $E$:

$$P_w = \frac{1}{\sigma} |J_e|^2 = \frac{1}{\sigma} |\epsilon E|^2. \quad (4)$$

2.1.2. Heat Conduction. The generated Joule heat $Q$ propagates inside the material, and the propagation process follows the formula:

$$\rho C_p \frac{\partial T}{\partial t} - \nabla (\sigma \nabla T) = Q, \quad (5)$$

where $\rho$ is the density of the material, $C_p$ is the specific heat capacity of the material, $T$ is the thermal conductivity of the material, and $t$ is the temperature of the material. In the experiment, the magnetic induction intensity $B$ around the infinite straight wire is defined by the formula:
\[ B = \frac{\mu I}{2\pi h}, \]  
where \( H \) is the distance to the straight wire. It can be obtained that the magnetic field strength of \( B \) decays rapidly with the increase of the distance to the coil. The thermal power in induction heating is proportional to the square of eddy current density, which can be obtained from (6).

### 2.1.3. Infrared Radiation

According to Stefan-Boltzmann’s law, an object whose temperature is higher than zero degree Kelvin will spontaneously generate infrared radiation outward.

\[ J^* = \varepsilon \sigma_{sb} T^4, \]  
where \( \varepsilon \) is the emissivity of the material, \( \sigma_{sb} \) is Stezmann-Boltzmann constant, and \( T \) is the absolute temperature.

### 2.2. Thermal Signal Reconstruction (TSR)

The reconstruction of thermal signal sequence is based on one-dimensional heat conduction equation, and the surface temperature response equation of applying instantaneous uniform excitation to thick materials is as follows:

\[ \frac{\partial^2 T}{\partial x^2} + \frac{1}{k} g(x, t) + \frac{1}{\alpha} \frac{\partial T}{\partial t} = 0, \]  
where \( g(x, t) = Q \delta(x) \delta(t) \alpha = \frac{k}{\rho c} \),

\[ T(t) = \frac{Q}{\varepsilon \sqrt{\pi t}}. \]  

Polynomial fitting is performed on it:

\[ \ln [\nabla T(t)] = \sum_{n=0}^{N} a_n \ln (t)^n. \]  

The original data is reconstructed when the coefficients \( a_n \) is fitted from Equation (11) as a function of the change of temperature with time at each point

\[ \nabla T(t) = \exp \left( \sum_{n=0}^{N} a_n \ln (t)^n \right). \]  

After reconstruction from Equation (11), differential operation can be performed, so that first-order and second-order differential can be performed. The image and differential obtained after reconstruction of any point of the heat map sequence are obtained by Equation (12). The thermal imaging image processed by TSR increases the spatial and temporal resolution of the thermal image. Between (1) and (5), it is known that the heat generated inside the tested material and its conduction are directly affected by the electrical conductivity and thermal conductivity of the material, and the temperature of the area where the wood material has metal matter will be significantly different from that of nondefective area. Radiation energy also has certain influence on thermal conductivity.

The location of metal area in the measured wood material can be observed from infrared thermal imaging to capture the surface temperature thermal image of wood material. At the end, TSR algorithm is used to process data to evaluate metal in wood. The TSR algorithm employs the temporal and spatial variation information of surface temperature to process the temporal information of each pixel in the thermal image sequence and transforms the temperature response curve of each pixel from the time domain to the logarithmic domain.

From Equation (12), it can be seen that the temperature change curve of the nonmetal area satisfies the linear relationship, and the temperature change curve of the metal area is nonlinear.

### 3. Experimental Study

The samples under test are two pieces of dry wood materials with a width of 42 mm. In Figure 2, two blocks contain different amounts of metal foreign matter, marked as L1 and L2. The physical diagram of eddy current thermal imaging system is shown as Figure 1. The power source of the excitation induction heating system is MDS-GLY-01, the input voltage is single-phase 220 V/50 Hz, the operation frequency is 150 kHz-250 kHz, and a circular excitation coil is adopted. Specification model of water cooling equipment is MDS-SL-03. For long-wave infrared thermal camera model, FLIR A655SC, its resolution is 640 × 480. The speed of full frame 16-bit data is 50 fps. The metal body-containing regions were placed under coil, and the excitation voltage was 58 V, the excitation current was 339 A, and the excitation frequency was 1055 Hz. The excitation time was 1500 ms.

### 4. Results and Discussion

After heating, the frame is selected. The obtained infrared thermal image has been analyzed. During the experiment, the environmental interference is eliminated. As can be seen from Figure 3, the temperature of metal-free wood area is blue area, which means temperature remains constant. The representing metal is at the red dot. The fitting graph of transient temperature is increasing with time. The locations of the metals can be determined from the infrared thermal images due to the effect of thermal diffusion whereas it is difficult to identify the real size of a metal.

The temperature rise in the excitation coil area without metal is almost the same. When there is metal in the specimen, the temperature rise curve with metal is obviously higher than that of without metal, and the temperature rise changes more when the metal is close to the excitation coil. At the end of heating, the temperature rise of the metal-free area and the metal area in L1 is about 14°C, and the temperature rise of L2 is about 24°C. It takes a certain time for metal in wood materials to affect the change of surface temperature. After the excitation time is over, the temperature of the metal drops
slowly, which is due to the poor heat dissipation of the wood material. The heat generated by the metal will be stored in the wood material for a certain period of time. Therefore, when the excitation time is over, the temperature of the metal area drops slowly, and the curve drops slowly. On the other hand, the temperature rise of metal material shows that the
metal in wood material has produced eddy current by excitation power supply. As a result, the eddy current density increases in the metal region. With stronger the induction intensity near the excitation coil, the smaller the eddy current density in the metal-free region. Therefore, the temperature characterization of the thermal imaging can be obtained by the eddy current method. It can effectively identify the location of metal in wood.

In this section, in order to evaluate the proposed algorithm, principal component analysis (PCA) and independent component analysis (ICA) algorithms have been selected for comparison. As shown in Figures 4 and 5, the temperature rise of the metal area is not obviously displayed in the image with PCA, and the position and size of the metal are blurred. Despite this, these algorithms can extract features effectively in detecting metals from ECPT system which have more obvious metal characteristics. The metals in the thermal images are relatively easy for human to discern.

After TSR, the results are shown in Figure 6. The temperature rise of metal in wood materials changes more obviously, and the position and size of metal foreign bodies are clearer. The temperature difference between metal and nonmetal decreases from inside to outside, the temperature rise in metal area increases obviously, and the surrounding temperature is decreasing, forming obvious temperature difference. As shown in TSR, that number of metal in L1 is 4 metals, the number of metal in L2 is 5 metals, and the area size represents the size of the metals. Experimental results shows that the location, size, and quantity of metal can be clearly identified.

The proposed method is compared with two state-of-the-art methods by using two samples. The evaluation metrics concern both efficiency (inference time) and effectiveness. The results are the mean of five different infrared thermal datasets. The same platform has been used to run them, and the results are given in Table 1. From Table 1, conclusions can draw that all algorithms can have certain improvements

### Table 1: Evaluation table for proposed method.

| Case | PCA   | ICA   | TSR  |
|------|-------|-------|------|
| L1   | 84.34%| 86.42%| 86.70%|
| L2   | 84.88%| 86.01%| 86.98%|
on metal detection, especially for the size detection. The results are achieving 2.34% and 2.1% gains.

5. Conclusions

At the present time, stress wave systems can only be used for qualitative testing. In this paper, eddy current thermography is used to detect metal in wood materials, and the detection principle and thermal signal reconstruction technology (TSR) are analyzed in detail. The conclusions are as follows:

(1) It can accurately detect the presence or absence of metal in wood and other materials and determine the quantity and size of metal

(2) Compared with other nondestructive testing, the effectiveness is reflected in the fact that there is no lift-off effect, the heating is rapid, the rapid detection is convenient, the detection area is large, the sensitivity is high, the use is convenient, and the influence of the shape and structure of the detected object is small

(3) High efficiency is reflected in the ability to accurately determine the position of metal in wood, obtain the size of metal, and greatly improve the production and processing efficiency and detection

However, the main limitation of proposed method is that the overall algorithm is complicated, and the amount of data is large, which requires more calculation and time. The subsequent algorithm and workflow need to be simplified to a certain extent to reduce the amount of calculation. With further research, this problem will be solved in the near future.

Data Availability

The datasets, codes, and weight files used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The work was supported by the National Natural Science Foundation of China (62071123, 61601125), the Natural Science Foundation of Fujian Province of China (2020J01312), the 2019 Fujian Provincial Marine Economic Development Subsidy Fund Project (FJHJF-L-2019-7), the Program for New Century Excellent Talents in Fujian Province University, and the cultivation plan of Outstanding Young Scientific Research Talents in Colleges and Universities of Fujian Province.

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