

Deep Learning-Enhanced Push-Broom Hyperspectral Imaging System for Non-Destructive Subsurface Defect Detection

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Abstract—This study presents a custom-developed push-broom hyperspectral imaging (HSI) system integrating a hyperspectral camera, halogen illumination, and a motorized linear translation stage with a C#-based interface. The system achieves a spatial resolution of 31.9 $\mu\text{m}/\text{pixel}$ (vertical) and 140.4 $\mu\text{m}/\text{pixel}$ (scan direction), with a spectral range from 367 to 1027 nm and a spectral resolution of 2.87 nm at 435.68 nm. A 3D hyperspectral data is processed by selecting diagnostically relevant wavelengths to reconstruct 2D perspective images. Deep learning and Gaussian Mixture Models are used for unsupervised feature extraction and defect classification. Experimental results demonstrate the system's ability to detect surface and subsurface structures, including concealed playing card patterns and internal cracks in the laser-annealed silicon carbide substrate, highlighting its potential for automated, non-destructive internal defect inspection.

Keywords—Hyperspectral Imaging, Push-Broom Scanning, Subsurface Defect Detection, Non-Destructive Testing, Deep Learning, Gaussian Mixture Model, Silicon Carbide.

I. INTRODUCTION

The detection of subsurface defects in materials is a critical challenge in the fields of semiconductor manufacturing, composite material evaluation, and structural health monitoring. Although traditional non-destructive testing (NDT) techniques—such as ultrasonic testing, X-ray imaging, and eddy current testing—are widely utilized and effective, they are often limited by spatial resolution, safety considerations, and stringent surface preparation requirements [1]. Additionally, X-ray Computed Tomography (CT) [2] and Optical Coherence Tomography (OCT) [3] have been employed for the non-destructive detection of microcracks and voids in wafer fabrication processes. CT offers excellent penetration and three-dimensional imaging capabilities but is constrained by high

equipment costs and operational complexity. In contrast, OCT provides high resolution and contactless imaging advantages, but its limited penetration depth presents challenges for detecting deep defects within thick structures or highly absorptive materials. In recent years, hyperspectral imaging (HSI) has emerged as a powerful alternative for material inspection [4,5], offering the ability to capture rich spectral-spatial information across a broad range of wavelengths, thereby enabling the identification of subtle chemical and structural anomalies beneath the sample surface.

Push-broom HSI systems, in particular, offer high spectral fidelity and spatial resolution, making them suitable for detailed surface and subsurface inspection tasks. However, most existing HSI systems are limited by their hardware constraints, lack of adaptability, or insufficient integration with modern machine learning techniques that can enhance interpretability and classification performance. Moreover, the detection of subsurface anomalies requires not only sufficient optical penetration into the material but also robust data processing pipelines capable of distinguishing latent defects from background variation.

In this study, we present a custom-designed push-broom HSI system for non-destructive subsurface defect detection, integrating a hyperspectral camera with a halogen light source and a linear translation stage for precise scanning. A control interface developed in C# enables flexible operation, including adjustable scanning speeds, data acquisition, and real-time image reconstruction. The system supports a wide spectral range from 367 nm to 1027 nm and is capable of characterizing optical properties of various materials. Spectral resolution, characterized by a full width at half maximum of 2.87 nm at 435.68 nm, confirms the system's capacity for fine spectral discrimination.

To enhance the performance of defect detection, a deep learning-based feature extraction method is

employed to analyze the reconstructed hyperspectral images. Convolutional Neural Networks (CNNs) extract image features through convolutional and pooling layers, initially capturing low-level attributes such as edges, textures, and shapes, and progressively integrating these representations to derive higher-level semantic information, thereby enabling accurate image recognition and classification [6]. The extracted features are subsequently classified using Gaussian Mixture Models (GMM) [7] within an unsupervised learning framework, enabling the identification of surface and subsurface anomalies without reliance on labeled datasets. Two validation experiments were conducted: one involving playing cards partially obscured by white paper to evaluate the system's penetration resolution, and the other using laser-annealed silicon carbide (SiC) substrates to assess its ability to reveal internal crack patterns. The system provides a compact, AI-enhanced HSI platform for automated subsurface defect detection, with strong applicability in materials science, semiconductor inspection, and industrial quality control.

II. SYSTEM ARCHITECTURE AND PERFORMANCE EVALUATION

We developed a push-broom HSI system integrating a hyperspectral camera, linear stage, halogen light, and a custom C# user interface. The system was operated on a laptop equipped with an Intel Core i7-13620H processor, 16 GB of DDR5 RAM, and an NVIDIA RTX 4050 GPU with 6 GB of dedicated video memory. This hardware configuration supports the delivery of high spectral resolution and spatial consistency, enabling the system to be effectively applied in high-precision material characterization and defect detection tasks. As illustrated in Figure 1, the core imaging module comprises an HSI-VNIR-E hyperspectral camera coupled with an Imperx GEV-B1621M industrial camera, featuring a sensor size of 9.02×8.8 mm and a spatial resolution of 1632×1232 pixels. The system is further equipped with a V10E-type 2/3" spectrograph, which decomposes incoming light into fine spectral bands. A 30 μ m entrance slit is employed to optimize light throughput and enhance spectral resolution.

The system's spectral range of 367–1027 nm encompasses the visible to near-infrared regions,

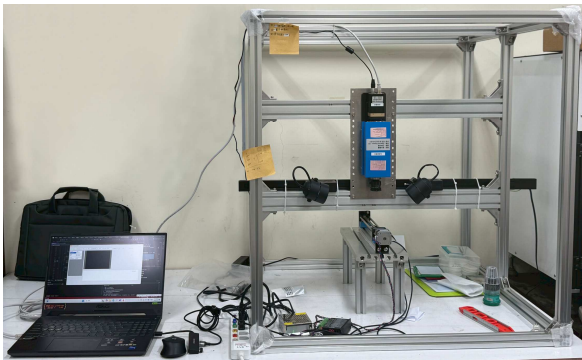


Fig. 1. Photograph of the assembled push-broom HSI system.

enabling versatile material characterization. During imaging experiments, the optical setup was configured with an aperture of $f/1.4$, an object distance of 115 mm, and a lens focal length of 7.12 mm, ensuring stable and high-fidelity image acquisition. Samples were conveyed by a motorized linear translation stage at a scanning speed of 3 cm/s to maintain spatial and spectral consistency across the acquired data. After systematic optimization of system parameters, the resulting spatial resolution was measured to be 140.4 μ m/pixel in the scanning (horizontal) direction and 31.9 μ m/pixel in the vertical direction (within the field of view). These values demonstrate the system's capability to resolve fine spatial details. Preliminary results confirm the system's high spectral resolution and wavelength-dependent penetration, supporting its use in precise spectral analysis, non-destructive subsurface inspection, and applications including NDT and biomedical imaging.

III. SAMPLE PREPARATION

In this study, a laser annealing process using a 532 nm wavelength laser was applied to 4H-SiC substrates to modulate the surface material properties. During the experiments, laser parameters including power (0.5 W), scan speed (200 mm/s), repetition frequency (20 kHz), and spot spacing (0.02 mm) were kept constant. The primary variable was the laser defocus distance, which was systematically adjusted to shift the focal point from outside the substrate surface to within the substrate, in order to investigate its influence on the annealing performance. Experimental results indicated that defocus distances of +0.35 mm and +0.40 mm yielded the most favorable annealing effects. For comparison, four additional conditions were tested, including in-focus (0.00 mm) and positive defocus distances of +0.41 mm, +0.42 mm, and +0.43 mm. Subsequent analysis using hyperspectral imaging revealed structural changes within the SiC substrate under different defocus conditions, demonstrating the potential of this approach for controlled modification of internal microstructures.

IV. HYPERSPECTRAL IMAGE RECONSTRUCTION ALGORITHM

This study aims to develop an algorithm that leverages hyperspectral data and the wavelength-dependent penetration properties of materials to simultaneously visualize surface and subsurface defects within a single two-dimensional image. By processing a 3D hyperspectral datacube, diagnostically significant wavelengths are selectively integrated to reconstruct 2D perspective images that encapsulate both surface morphology and internal structural variations.

This study proposes a HSI-based reconstruction framework designed to extract representative spectral features from high-dimensional wavelength data and synthesize a two-dimensional image that retains both spatial and spectral relevance. The detailed procedure is as follows:

A. Hyperspectral Data Unfolding and Image Reconstruction

The datacube acquired from samples is unfolded along the spectral axis, generating a total of 1232 single-wavelength images. Each image corresponds to a specific spectral band spanning from the visible to the near-infrared range, reflecting the material's spectral response across wavelengths.

B. Image Sharpness Evaluation and Selection

To identify images with rich structural content, the Laplace variance metric is applied as an indicator of image sharpness [8]. This metric quantifies the intensity of edge information within each image: higher variance values indicate sharper images with abundant detail, while lower values suggest blurring or lack of distinguishable features.

C. Deep Feature Extraction

The selected high-sharpness images are subsequently input into a ResNet-50 convolutional neural network [9]. By leveraging its deep hierarchical architecture—comprising convolutional, pooling, and fully connected layers—ResNet-50 automatically extracts both local and global features, yielding high-dimensional feature vector representations for downstream analysis.

D. Image Feature Classification

The feature vectors obtained from the ResNet-50 are subsequently classified using GMM. GMM models the data as a combination of multiple Gaussian distributions and estimates model parameters via the Expectation-Maximization algorithm. This probabilistic approach enables soft clustering and is widely applied in image segmentation and pattern recognition tasks.

E. Representative Image Selection and Reconstruction

Based on the clustering results from the GMM, one representative image is selected from each cluster. These selected images are then combined to reconstruct a final two-dimensional fused image, effectively integrating both surface and sub-surface structural information.

V. EXPERIMENTAL RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed hyperspectral data reconstruction algorithm, we conducted experiments on two distinct sample types. The first experiment involved a colorful playing card partially covered by a sheet of white paper. It is known that certain wavelengths of light can penetrate the paper, allowing the obscured patterns on the card to be partially revealed. Moreover, because the card is multicolored, specific features become visible or invisible depending on the wavelength, making this setup suitable for assessing the algorithm's ability to reconstruct spectral information across different bands.

The second experiment focused on the reconstruction of hyperspectral data obtained from annealed SiC substrates. The objective was to determine whether the algorithm could reveal internal defects within the

substrate structure, which are often not directly observable through conventional imaging techniques.

A. Experiment One: Covered Playing Card

Figure 2 presents the photograph of a colored playing card alongside reconstructed images captured at wavelengths of 500 nm, 662 nm, and 750 nm. It can be observed that light at 500 nm and 662 nm is unable to penetrate the white paper, rendering the obscured patterns beneath it invisible. In contrast, light at 750 nm possesses greater penetrative capability, allowing the underlying patterns to be revealed. Additionally, both 662 nm and 750 nm wavelengths are effectively reflected by the red and yellow regions of the card, which appear as white areas in the reconstructed images. Conversely, light at 500 nm is more readily absorbed by these colored regions, resulting in their depiction as dark gray in the corresponding image.

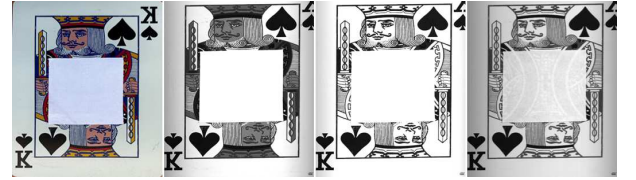


Fig. 2. Playing card and reconstructed images at 500 nm, 662 nm, and 750 nm, showing light penetration and color reflection effects.

Figure 3 presents the final composite images generated through the fusion of multiple single-wavelength reconstructed images. During the fusion process, local image sharpness was assessed, and the three sharpest reconstructed images were selected and combined using weighted averaging based on their relative sharpness. The image on the left was processed using a 6×6 window, the middle with a 5×6 window, and the right with a 3×3 window. It can be observed that as the window size decreases, the overall image quality improves, which can be attributed to the enhanced sensitivity of smaller windows in capturing local sharpness variations. However, due to theoretical and practical limitations, the minimum feasible window size for computing Laplacian variance is 3×3 , thus precluding further improvements in image quality through window size reduction.

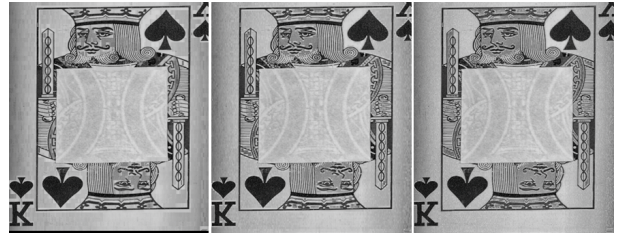


Fig. 3. Composite image fused from single reconstruction images, showing improved sharpness with decreasing window size, down to the 3×3 limit.

The fused image of the playing card illustrates that the proposed hyperspectral image reconstruction algorithm effectively integrates features such as edges, lines, and cracks from single-wavelength reconstructions, thereby enhancing overall image quality and visual fidelity.

B. Experiment Two: Laser-annealed SiC Substrates

In Experiment 2, we retained the image reconstruction workflow and parameter settings established in Experiment 1 but introduced a refined strategy for selecting representative images within each cluster. In the initial experiment, we observed that images grouped into the same category by GMM exhibited strong spectral proximity, often forming clusters composed of adjacent or sequential wavelengths. Consequently, the representative image for each cluster in Experiment 1 was chosen as the one corresponding to the central wavelength within that spectral range.

To further investigate the impact of representative image selection on the quality of reconstructed results, Experiment 2 introduced an alternative selection criterion. Specifically, we selected the image with the highest Laplace variance within each cluster as the representative, aiming to enhance the structural detail and visual sharpness of the final composite image. This modification enabled us to systematically assess the effect of different selection strategies on the fidelity and effectiveness of hyperspectral image synthesis.

Figure 4 presents comparative images of a non-annealed sample (center) and annealed samples under positive defocus conditions of +0.35 mm (left) and +0.40 mm (right). The top row shows the photographs of the samples, while the middle and bottom rows display the hyperspectral fused images reconstructed using the conventional image selection method (Experiment 1) and the improved strategy proposed in this experiment, respectively. Notably, both fused images successfully reveal microcracks beneath the surface of the SiC substrate—defects that are indiscernible in standard optical images. Furthermore, the images reconstructed using the proposed selection method demonstrate enhanced clarity and structural detail, indicating superior potential for visualizing subsurface defects and advancing non-destructive evaluation applications.

The same hyperspectral image reconstruction methodology was applied to assess additional annealed samples. Figure 5 presents comparative images of a non-annealed sample (center) and samples treated with laser annealing at positive defocus distances of +0.41 mm (left) and +0.42 mm (right). The top row shows the photographs of the samples, while the bottom row displays the hyperspectral fused images generated using the proposed image selection strategy. The results indicate the presence of internal microcrack structures in both annealed samples, with the +0.42 mm condition

exhibiting evident surface damage, suggesting

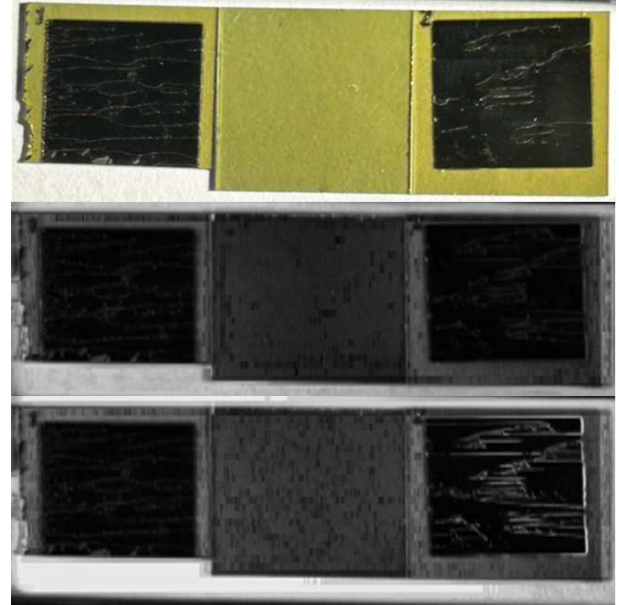


Fig. 4. Comparison of annealed and non-annealed samples. The improved method enhances subsurface defect visualization.

significant thermal effects induced by the laser treatment.

Figure 6 illustrates a comparison between the non-annealed sample (center) and those processed under focal distance +0.00 mm (left) and positive defocus +0.43 mm (right). Although the photographs (top row) clearly display pronounced surface damage in both annealed samples, the corresponding fused hyperspectral images (bottom row) do not reveal internal microstructural features, likely due to the extensive surface degradation impeding light penetration and thus preventing acquisition of subsurface information. These findings imply that the applied laser parameters under these two conditions are unsuitable for modulating

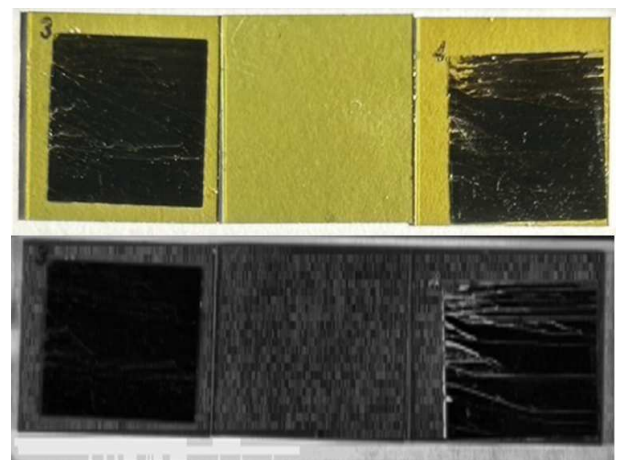


Fig. 5. Comparison of a non-annealed sample (center) and laser-annealed samples at +0.41 mm (left) and +0.42 mm (right) defocus, highlighting microcracks and thermal effects.

subsurface properties of the SiC substrate and may instead cause detrimental surface alterations.

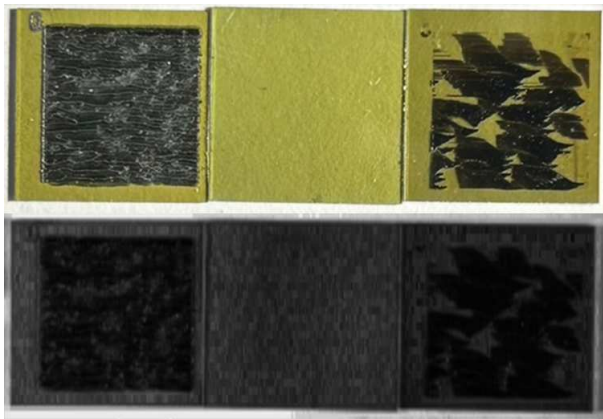


Fig. 6. Comparison of non-annealed and annealed samples at +0.00 mm and +0.43 mm defocus, highlighting surface damage and limited subsurface visibility.

VI. CONCLUSION

This study successfully developed a push-broom HSI system and demonstrated its potential for detecting both surface and subsurface defects in materials. By employing a hyperspectral image reconstruction algorithm, we effectively analyzed the influence of laser annealing on the internal structure of SiC substrates, revealing the modulation effects of various laser parameters on material properties. Experimental results indicated that appropriate defocus distances (+0.35 mm and +0.40 mm) significantly enhanced the annealing outcome, whereas other conditions (0.00 mm, +0.41 mm, +0.42 mm, +0.43 mm) led to surface damage or failed to induce meaningful subsurface modifications. Moreover, the improved image selection strategy enhanced the clarity and structural detail of reconstructed HSI images, thereby advancing the precision of non-destructive inspection. The playing card masking experiment further validated the system's subsurface imaging capability, demonstrating its adaptability across different material types. Future work will focus on optimizing the reconstruction algorithm to further improve image fidelity and structural resolution, while also expanding its application in semiconductor

analysis, biomedical diagnostics, and agricultural inspection. Additionally, advanced HSI data analysis techniques will be developed to enable characterization of depth-resolved defect structures within samples.

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