A REVIEW ON HYPERSPECTRAL IMAGING AND ITS APPLICATIONS IN WOOD DOMAIN

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Abstract

Hyperspectral imaging (HSI) has proven to be a highly effective tool across a wide range of military, environmental, and civil applications over the past thirty years. Modern remote sensing techniques provide extensive coverage of large areas on Earth, offering both high spatial and spectral resolutions. These capabilities enhance HSI's effectiveness in remote sensing applications, particularly for identifying materials and analyzing complex surfaces with detailed spectral data. In recent years, HSI has gained significant attention in fields such as food safety and quality assessment, medical diagnostics, and agricultural analysis. This review explores the fundamental principles of HSI and its applications specifically within the wood industry. Numerous researchers have proposed promising solutions for automatic systems utilizing HSI. Researchers in the field of hyperspectral imaging (HSI) are exploring several aspects of wood analysis, including: wood classification, wood species or fungi detection, wood segmentation. By using these methods, researchers can achieve more precise and reliable results in wood analysis, contributing to advancements in forestry, conservation, and the wood industry. This review can serve as a foundation for future research and advancements, particularly in the wood domain.

Keywords: **Hyperspectral imaging; Spatial and Spectral Resolution; hyperspectral wood images.**

1. Introduction

Over the years, Hyperspectral Imaging (HSI) technology [3] has seen continuous development and has been applied across diverse fields. Recently, many researchers have started utilizing HSI to detect and analyze wood properties. Given the high dimensionality and large scale of hyperspectral images, variable selection algorithms are essential for minimizing redundancy and identifying the most informative wavelengths. HSI has been employed in various wood industry applications, including predicting moisture content, estimating wood density, classifying sapwood and heartwood, and recognizing different wood species. This review provides an overview of the fundamentals of hyperspectral imaging (HSI), discusses the commonly used technologies in HSI, and highlights the innovative applications of HSI in wood manufacturing, wood classification, iwood segmentation, and other wood-related imaging studies. This review is aimed at students working on research or projects related to wood hyperspectral imaging (HSI), as well as researchers interested in exploring wood HSI images. It also serves as a resource for those in the wood domain who are looking for methodologies, such as

deep learning and SVM, to enhance their studies and applications.

1.1. *Hyperspectral imaging fundamentals*

Hyperspectral imaging (HSI) is a technique that captures spectral information for each pixel in an image, enabling detailed analysis. HSI sensors, such as imaging spectrometers, typically cover near-infrared, visible, and short-wavelength infrared spectra within the 0.4 to 2.5 µm range. These sensors with narrow band systems are capable of producing spectral data at hundreds of distinct wavelengths, making HSI a valuable tool for classifying earth surface materials and enabling a wide range of applications. Unlike RGB or grayscale images that have three or more bands or channels, HSI data consists of numerous bands or channels and is represented as a 3D hyperspectral cube, with one spectral dimension and two spatial dimensions [1].

The data can be categorized by spatial and spectral information or by the method of acquisition. Techniques for acquiring HSI data include point scanning (whiskbroom), line scanning (push broom), staring imagers, and snapshot imagers [8]. Point scanning involves moving the detector or sample in the spatial dimension to scan a single point, providing high spectral resolution and flexibility regarding optical setup, sample size, and spectral range. Line scanning, used primarily in remote sensing, captures one-dimensional spectral data across pixels on a platform, such as a satellite or airplane, creating a hyperspectral 3D cube with spatial and spectral information. Image staring, or spectral and area scanning, uses a 2D array detector to capture scenes with separate exposures, while snapshot imaging uses different integration times to construct a hyperspectral 3D cube without scanning.

Qian [2] outlines three main methods for obtaining hyperspectral cube data using different spectrometers: snapshot HSI, spectral filter-based methods, and dispersive-element-based methods. To acquire hyperspectral images with varying temporal and spatial resolutions, sensors must be mounted on different platforms like close-range platforms, airplanes, and UAVs. Hyperspectral images are characterized by their spectral and spatial resolution, with spectral resolution detailing pixel variation as a function of wavelength and spatial resolution defining the geometric relationship between image pixels. HSI data is generated by imaging spectrometers, which have evolved through the combination of remote imaging and spectroscopy, the latter being the study of light emitted or reflected by materials and its energy variation with wavelength. Spectrometers can measure spectral bands as narrow as 0.01 µm across a wide wavelength range, typically from 0.4 to 2.4 µm, providing detailed spectral information. Hyperspectral imaging spectral region and their applications [5-7] are summarized in Table 1.

1.2. *Hyperspectral imaging fundamentals*

The smallest detectable detail in an image is known as spatial resolution, which is the measurement of the smallest feature that can be recognized as a separate entity. Both the sensor's design and its positioning above the surface have an impact. In actuality, spatial resolution—rather than pixel count—determines visual clarity. The design of the sensor, especially its height and range of view, affects the spatial properties of a picture. Energy from a specific area of the ground is detected by a distant sensor; the more comprehensive the spatial information, the smaller the area and the inverse relationship between size and spatial resolution. Only when the cell dimensions are appreciably smaller than the object's size can shape detection be accomplished [9]. Spatial resolution enables the identification of linear features that are more precise than the size of a single cell, such as individual fungi in a wood board.
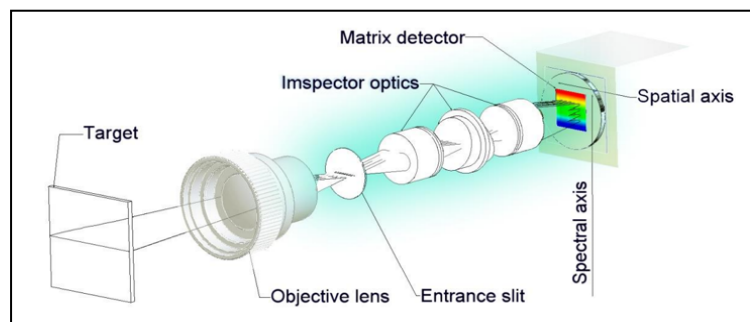

Fig 1. Hyperspectral imaging system. Image from [18]

Spectral region	Spectral range (nm)	Optimal observations
Thermal Infrared (TIR)	8000 - 15000	Heat sources, land and sea surface temperatures, geothermal mapping, thermal surveys
Infrared (IR)	6000 - 7000	Water vapor, soil moisture, cloud cover, thermography, forest fires and hotspots
Mid-wave Infrared (MIR)	3000 - 5000	Mineral and soil mapping, sea surface temperature, ice formations, geothermal and volcanic activity,
Short-wave Infrared (SWIR)	1100 - 3000	Vegetation mapping, dynamics and physiology, cloud and rock type
NIR (Near Infrared)	700 - 1100	Vegetation vigour, crop and soil moisture, rock and mineral type
Visible	400 - 700	Shallow coastal and coral reef bathymetry, vegetation type, land cover, urban development, ocean color
Ultraviolet (UV)	100 - 400	Ozone concentration, coral reef health, aerosol distribution, pollution

Table 1: Hyperspectral imaging spectral region and applications [5-7]

1.3. *Spectral Resolution*

Spectral resolution refers to the range of the electromagnetic spectrum covered and the number of spectral bands measured by a sensor. A sensor may cover a wide frequency range but have a low spectral resolution if it captures only a few spectral bands. Conversely, a sensor that is sensitive to a narrow frequency range but captures a large number of spectral bands has a high spectral resolution, allowing it to distinguish between scenes with similar or nearly identical spectral signatures. Multispectral images typically have low spectral resolution and are thus unable to detect subtle spectral signatures within a scene [10]. Hyperspectral imaging (HSI) sensors, on the other hand, capture images in many contiguous, very narrow spectral bands across the visible, near-infrared, and mid-infrared portions of the electromagnetic spectrum. This advanced imaging capability offers significant potential for identifying materials based on their unique spectral signatures. An HSI sensor with a high spectral resolution can provide much more detailed information about a surface's material than standard spectral ranges.

1.4. *Advantages and disadvantages of hyperspectral wood imaging*

The advantages of using hyperspectral imaging in wood domain are as follows:
- Hyperspectral images have proven particularly effective in identifying individual tree species and distinguishing between multiple subspecies of the same species [11].
- Near-infrared hyperspectral imaging (NIR-HSI) can be used to assess inter-annual wood density and predict wood density at a future age to evaluate the accuracy of early selection [12]
- The experiments do not use any chemicals, making them environmentally safe.
- It simultaneously acquires spatial and spectral information, offering more precise and accurate data about chemical samples from the relevant platforms, which improves the ability to refine data and conduct further experiments.

The disadvantages of using hyperspectral imaging in wood domain are as follows [1]:
- A hyperspectral imaging system is significantly more expensive compared to other image processing techniques.
- Detecting and identifying different items within the same image using spectral data is challenging unless the various objects have unique absorption features.
- Due to the large data size of hyperspectral imaging, there is a need for high-speed computers to process the data and large-capacity drives for storage.

2. Hyperspectral Wood Images Applications

Researchers use hyperspectral imaging (HSI) to analyze spectral information and differentiate between wood species, which aids in forestry management, timber trade, and conservation. HSI also helps in detecting specific wood species and fungal infestations, as each species and fungus has unique spectral characteristics. This technique is crucial for quality control, preventing disease spread, and ensuring proper wood usage.

Additionally, wood segmentation with HSI divides images into meaningful regions, such as sapwood and heartwood, or identifies defects, helping assess wood quality and its suitability for different applications.

Applications using wood hyperspectral images can generally be classified into two main branches based on their focus on either spatial resolution or spectral resolution. Both spatial and spectral resolution are essential for different types of analyses and applications involving wood hyperspectral images. The choice of focus depends on the specific requirements of the application, whether it is more critical to have detailed spatial information or to differentiate between materials and conditions based on their spectral characteristics.

3. Methodology

3.1. *Methodology of HSI Images Applications in Spatial Branch*

Researchers have conducted specific studies using hyperspectral imaging, particularly focusing on the spatial branch, in areas such as wood production, wood detection, and wood classification. In this paper [13], they introduce a spatial classifier to classify wood categories of HSI images developed by adapting the input and output units of a conventional CNN-based image classifier, like Cifar10Net. Their approach has proven effective in addressing existing challenges of HSI dataset in wood industry and advancing the current state-of-the-art. The results, in terms of accuracy and training time, indicate that the proposed classifier can be trained with limited training data and minimal computational resources. In [14], the proposed segmenter can accurately predict heartwood and sapwood areas on wood board hyperspectral images especially in spatial branch. Additionally, they demonstrated that training the encoder part of the segmenter is not necessary. Addition, the researcher in [15] proposed a spatial branch classifier of wood fungi dataset. The results indicate that the proposed framework is both lightweight and effective for recognizing wood fungi categories. It outperforms a benchmark classifier by 17% and achieves an accuracy of 96% in generating classification maps for hyperspectral images of wood boards, regardless of their size.

Acetylation is a chemical treatment used to enhance wood's hygroscopic properties, but its effects on wood's hierarchical structures are not well understood. Traditionally measured gravimetrically, acetylation provides a general estimate but lacks detail on specific wood regions. Using hyperspectral near-infrared imaging [16], they found notable differences in acetylation between earlywood and latewood, indicating varying acetylation times for these cells. Our cluster analysis of Raman images further revealed chemical differences at the wood cell level, advancing our understanding of how chemical treatments affect wood's hierarchical structures. The Raman images were analyzed using PCA and PCA-based pixel cluster analysis after combining the earlywood and latewood images into a mosaic. Researchers are focusing on analyzing the spatial patterns and textures in the HSI images. Spatial information is crucial for understanding the physical structure and arrangement of wood fibers and detecting patterns associated with defects or fungal infections.

3.2. *Methodology of HSI Images Applications in Spectral Branch*

Concentrates on the spectral data, which captures the light absorption and reflection properties of the wood across different wavelengths. Spectral analysis provides insights into the chemical composition and moisture content of the wood, as well as identifying specific species and any presence of fungi. The project of segmenting sapwood and heartwood of oak boards, authors proposed an investigation that hyperspectral imaging was employed instead of traditional RGB cameras. To enhance the amount of information obtained from the boards, using sapwood heartwood oak data, deep learning models, specifically U-Net and U-within-U-Net architectures, along with various spectral dimensionality reduction techniques, were developed to segment boards into heartwood and sapwood. The effectiveness of these deep learning models was compared against Partial Least Squares Discriminant Analysis (PLS-DA) and Support Vector Machines (SVM). PLS-DA, previously utilized at MiCROTEC, served as a baseline model for comparison in this study [17].

The spectral classifier to classify wood fungi categories is trained in phases using selected training samples. To minimize the impact of noisy data, the training data is divided into groups based on classification scores from a simple classifier, such as a neural network, SVM, or random forest. Three data groups are formed with probability scores of 90-100%, 80-90%, and 70-80% [15]. In this study, [19] they utilized near-infrared hyperspectral imaging to predict the moisture distribution on wood surfaces at a macroscale. Near-infrared spectra were obtained from the surfaces of conditioned wood samples, and principal component analysis was used to extract valuable chemical information from the spectral data. Dynamic vapor sorption isotherms confirmed the variations in moisture content between earlywood and latewood cells. Their findings highlight the effectiveness of hyperspectral imaging for process analysis in the modern wood industry. Additionally, a partial least squares regression model was developed to predict moisture content on wood surfaces, demonstrating that hyperspectral near-infrared imaging can accurately predict moisture variations across wood surfaces.

Hyperspectral near-infrared imaging was used in a field study to monitor fungal growth on various wood substrates exposed outdoors for six months. This study extended previous laboratory research on fungal growth

on wood surfaces, comparing indoor and outdoor measurements to assess the impact of different lighting conditions. Techniques like principal component analysis, spectral angle mapper, and partial least squares-discriminant analysis were used to segment mold growth on wood surfaces and to generate growth curves over time. However, challenges arise due to wood characteristics like growth rings, knots, and cracks, which cause variations in spectra and fungal growth. To address these challenges, partial least squares-discriminant analysis is suggested for classification. Additionally, outdoor wood exposure leads to color changes from lignin photodegradation, wetting, leaching, and fungal discoloration. Hyperspectral technology shows promise for studying these effects, and future research aims to model and differentiate the factors contributing to wood color degradation [20].

4. Comparison of Experiment Results

This section discusses about different authors proposed methods and their key contributions. Table 2 shows the summarization of the experiment results on this review.

Applications	Key Contribution	Accuracy	Reference
Sapwood and Heartwood Classification	This paper proposed an adapting Convolutional Neural Network to develop Hyperspectral Spatial Classifier	92.49%	P.P.Htun, etc. (2021)
Sapwood and Heartwood Segmentation	The author proposed the process of generating a segmenter by modifying HSIs spatial classifier	92.59%	P.P.Htun, A. Htwe, T. Tillo, (2023),
End to End framework for wood fungi classification	The authors generated an End to End framework for classification of wood fungi by simulating both spatial and spectral resolution	96%	R. Confalonieri (Member, IEEE), P. P. Htun, B. Sun, T. Tillo, (2024)
Quantitative prediction of moisture content distribution in wood by using near-infrared hyperspectral imaging	They used near-infrared hyperspectral imaging to predict moisture distribution on wood surfaces at a macroscale. This was achieved by varying wood moisture content through acetylation and relative humidity control, measuring near-infrared spectra, and applying principal component analysis to the data.	Dynamic vapor sorption measurements 8.5% and 17% WPG. The false-colored predicted the middle sample with 8.5% WPG at 75% relative humidity.	Muhammad Awais, Michael Altgen, Mikko Ma¨kela", Tiina Belt1 and Lauri Rautkari, **(2022)**
Heartwood and Sapwood Segmentation	This thesis project at MiCROTEC focused on automating the detection of heartwood and sapwood in oak boards using hyperspectral imaging and deep learning models, such as U-Net and U-within-U-Net architectures. These models were compared against PLS-DA and SVM to improve the classification of wood attributes for more efficient production.	Their result increased the F1-Score from 0.730 for the baseline classifier PLS-DA to an F1-Score of 0.918,	Samuel Hallin Simon Samnegård, (2023)
"Hyperspectral imaging and chemometrics reveal wood acetylation on different spatial scales"	This study used hyperspectral near-infrared imaging to analyze acetylation effects on wood surfaces, revealing significant differences between earlywood and latewood. The findings highlight that earlywood and latewood cells may require different acetylation durations, advancing the understanding of chemical treatment effects on wood's hierarchical structures.	Their results get a range of 17.6% WPG makes their spectral calibration model	Mikko Ma¨kela¨, Michael Altgen, Tiina Belt, and Lauri Rautkari, (2021)
"Hyperspectral near Infrared Imaging of Wooden Surfaces Performed Outdoors_Indoors"	The authors used Hyperspectral near-infrared imaging to study fungal growth on wood substrates in outdoor environments. The research explored the impact of different lighting conditions and used methods like PCA, spectral angle mapper, and partial least squares-discriminant analysis to segment mold growth.	-	I. Burud, L.R. Gobakken, A. Flø, a T.K. Thiisa and K. Kvaala, (2015)

Table 2. Comparison among different proposed methods

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5. Conclusion

In conclusion, this review of hyperspectral imaging (HSI) in wood applications offers a comprehensive overview of the methodologies, algorithms, challenges, advantages, and drawbacks of using HSI, as well as potential areas for improvement in wood manufacturing. Recent applications have leveraged HSI to inspire further research. Various mathematical algorithms and tools, including classification, segmentation, anomaly detection, and efficient computation, have been explored to enhance HSI data analysis. The review emphasizes the role of HSI in enhancing accuracy and quality assessment in the wood industry. Researchers have proposed promising solutions for automated systems utilizing HSI, and future research could build upon this review to advance wood-related applications.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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