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Research Article

Multivariate Image Analysis Applied to Cross-Laminated Timber: Combined Hyperspectral Near-Infrared and X-ray Computed Tomography

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Engineered wood products, such as cross-laminated timber (CLT), are becoming more popular in the designs of modern sustainable buildings. This increased production of CLT requires more robust, yet less labour-intensive means to assess the material characteristics of whole CLT panels. In exploring ways of improving efficiency, this study explores multivariate image analysis (MIA) via partial least squares discriminant analysis (PLS-DA) machine learning as a means to classify CLT material features. CLT panels underwent nondestructive testing using near-infrared (NIR) hyperspectral imaging and X-ray computed tomography (CT) analysis. MIA was performed on these results to build predictive models for wood features, such as fibre alignment and knot type. The models showed that it was possible to classify material features on the surface of CLT using NIR alone; whilst when combined with X-ray data, it enhanced the predictive ability of material features throughout the CLT volume. These first results from such modelling have the potential to help map the chemical and physical material properties of CLT, improving the manufacturing efficiency of the product and allowing greater sustainability of engineered wood products.

1. Introduction

The European Standard EN 16351 defines cross-laminated timber (CLT) as a structural panel composed of orthogonally bonded layers of timber [1]. Owing to its compatibility with prefabrication, its potential to integrate into large assemblies, and its unrivalled design flexibility, CLT is gaining popularity as a sustainable building material in the global construction space [2]. With inherent dimensional stability coupled with high load-bearing capacity, CLT is superior to conventional nonengineered construction timber [3]. From a performance perspective, traditional wood buildings lag behind concrete and steel buildings due to the natural variance in material properties [3, 4]. CLT, which can be assembled into multilayer, load-bearing structures, can address some of the drawbacks of traditional timber and pave the way for wood-based large and high-rise structures that are more sustainable than steel and concrete alternatives. However, the contribution of specific material characteristics influenced by features, such as knots, to the overall performance of CLT panels is not well understood [5]. Thus, understanding the relationships between CLT material characteristics and performance is critical to defining applications, refining existing fabrication processes, and minimising material wastage to maximise value-yield. The variance of panels can be reduced, and their overall mechanical performance mean value can be enhanced [6].

Converting wood into engineered wood products like CLT panels increases the value of the constituent wood, which is a driving incentive to invest in new technologies that refine CLT properties. Not only does this enhance safety and longevity of the product [7], it also provides a competitive advantage over other market players [8]. Wood quality is a function of the occurrence of wood-moulding features and is dependent on their number, position, and size. Knots, the most influential nonhomogeneous features can be classified using different strategies [9]. Valuable handbooks on multivariate hyperspectral imaging and image analysis have been published [10–13]. A variety of strategies can be used for feature classification [9]; however, to reduce variance of the product, measurement technology for material assessment needs to be further developed [14]. The fact that end users contact CLT manufacturers with increasing frequency to enquire about appearance changes that have occurred highlights the importance of the situation. In fact, inspectors are unsure as to how they should evaluate CLT surfaces and link evaluation results with those obtained from final inspection. This is especially challenging as inspectors need to be able to provide realistic expectations based on classified wood features, like knots, increasing the risk of costly claims cases pertaining to CLT [15].

Currently, different noncontact methods exist to assess logs and lamellas for their quality [16]. However, there are no noncontact inspection methods based on imaging that allow continuous monitoring of the final CLT product. Image processing based on surface data and X-ray computed tomography (CT) data can identify material variations, boundaries, and dimensional changes in wood. Such image-based systems can eliminate the need for contact measurements, thus improving quality control and productivity and, in turn, reducing material waste. One problem, however, is that the characteristic values adopted for structural design are prone to substantial material variance. Numerous parameters that influence material quality are not taken into consideration due to the natural complexity of wood, which creates wide variances in these parameters [17]. However, multivariate image analysis (MIA) via principal component analysis has been successfully used for classifying features on wood surfaces based on surface images obtained at different wavelengths in the visible and near-infrared (NIR) spectrum [18].

The classification of knots based on X-ray data were demonstrated using two methods with similar results: a neural network model and a partial least squares projection to latent structures (PLS) model [19]. Hyperspectral imaging based on NIR spectroscopy, which allows for measurement of a broad range of chemical and physical properties, is promising for a wide range of industrial applications, including assessment of wood [20]. Sandak et al. [21] used hyperspectral imaging to develop models that quantify changes in chemical composition of the wood surface, aid process optimisation, and determine material properties.

NIR hyperspectral imaging calibrated with micro X-ray densitometry has been used to determine the ratio of mature to juvenile wood in pine [22]. This ratio is relevant for structural wood applications because of the differences in material properties. However, it is worth noting that the optimal NIR results were obtained when the transition points between earlywood and latewood were assessed separately through PLS discriminant analysis (PLS-DA). In another study [23], the density and microfibril angles of wood were determined with NIR hyperspectral imaging. The latter properties are invaluable as they are associated with wood stiffness and strength. In this instance, PLS regression analysis was performed to determine the relationship between X-ray densitometry and NIR spectroscopic data, which facilitated the detection of annual growth ring features in addition to heterogeneous features affecting wood quality. Importantly, the PLS approach enabled the correlation of NIR spectral data with density and microfibril angle. NIR and X-ray scanning have also been used for mapping the chemical and physical properties of end grain Poplar round log disks [24].

For large-scale production of CLT products, more accurate final quality control is required. Accurately predicting the influence of nonhomogeneous features on the mechanical properties of the finished product can lead to greater value-yield. When it comes to surface quality, CLT used for visible surfaces has the highest requirement, and thus, it is expected to have a homogeneous surface with minimal dead knots of relatively small diameters [15]. Predictably, the second highest CLT surface quality corresponding to industrial surfaces may exhibit more defects than CLT used for visible surfaces, and the lowest quality assigned to CLT used for nonvisible surfaces has the most extreme defects, ranging from rot-attacked knots, knot holes, and no limitations on knot diameters [15].

It is not uncommon for a single production line to produce more than 100 000 m^3/year of CLT. In response to the growing demand for CLT, the technology for quality assessment needs to keep up with the pace of creation of the large throughput CLT manufacturing facilities. Thus, noncontact process assessment, such as that proposed in this study, can add value to this growing industry. As the first novel CLT assessment based on pixel-level spectral image data, this research is intended to inspire further studies and potentially offer practical image-based CLT assessment techniques. Accurately and efficiently identifying factors that affect the properties of CLT requires classification of the variables involved from a data-driven perspective. As such, this research objective was to determine if multivariate image analysis based on NIR and X-ray data can facilitate enhanced classification of material features of CLT panels.

2. Materials and Methods

2.1. Materials. The CLT panels used in this study were composed of Norway spruce (*Picea abies* (L.) Karst.) and were fabricated at the old industrial CLT production line at Martinson, a part of Holmen Wood Products Sawmill (Bygdsiljum, Sweden). The panels were layered crosswise and bonded with melamine-urea-formaldehyde (MUF) adhesive (Cascomin 1247 with hardener 2526, Akzo Nobel). The adhesive was applied via an industrial line spreader on one side of each wood layer. A total of 320 g/m^2 adhesive was applied. The timber class corresponded to C24 grade [25] and consisted mainly of sapwood. Prior to use, CLT specimens were stored in a climate chamber accredited by RISE until an equilibrium moisture content of 12% was attained at a density of 480 kg/m^3. Six specimens were analysed; each specimen was a five-layered CLT. Specimens were assessed using two scanning systems: NIR spectroscopy and X-ray CT. All CLT specimens measured 30 mm × 95 mm × 240 mm. Three reference holes were drilled into each specimen's upper region. Using such reference features is good practice in an exploratory image-based study to simplify the initial control by ensuring that no data has been mirrored between different scanning systems [9].

2.2. Methods and Instrumentation. Increasing the number of variables generated from different wavelengths has the advantage of enabling more rotation in multivariate space. This was demonstrated by adding different filters to a digital camera [26]. This research intended to assess the effectiveness of MIA for building predictive models based on combining NIR and X-ray data (Figure 1).

2.2.1. Near-Infrared Imaging. Images were acquired using a hyperspectral short-wave infrared (SWIR) camera, model SWIR 3 spectral camera line inspector HSB, with a C-mount OLES15 15 mm lens at f/2.0 aperture. This multipurpose imaging system was manufactured by Prediktera AB (Umeå, Sweden) and works in push-broom mode, collecting data in the 1000–2500 nm spectral region from specimens passing along on a conveyor belt. The instrument was calibrated using a white reference panel and a simulated dark reference, which was done by temporarily closing the shutter. NIR hyperspectral images originating from 384 spatial pixels and 288 spectral bands were acquired; representing a scanned field of view (FOV) of 384 pixels × 677 pixels, which corresponds to 165 mm × 291 mm. In turn, one pixel data point corresponds to 0.43 mm × 0.43 mm × 288 spectral bands of the scanned CLT.

2.2.2. X-ray Computed Tomography Imaging. The CT scanner was a medical CT scanner with a sliding gantry on rails that had been adapted for use with wood material, namely, a Siemens Somatom Emotion Duo Sliding Gantry CT 2006A H-SP-CR (Munich, Germany). Scan parameters were prepared using convergence studies and were set to 110 kV, 67 mAs, craniocaudal, reconstruction kernel B70s L7T0 2, and the slice thickness for each scan was 2 mm. After each scan series, the scanner reconstructed greyscale images of 512 pixels × 512 pixels, representing a scanned field of view (FOV) of 500 mm × 500 mm. One reconstructed density voxel exported from the Siemens clinical CT scanning software corresponds to 0.98 mm × 0.98 mm × 2 mm of the scanned CLT.

2.3. Multivariate Image Analysis. All images were warped in MATLAB 2017 (MathWorks, Inc., Natick, Massachusetts, USA) to correspond to the same matrix size. Subsequently, MIA was performed using Prediktera Evince Professional version 2.7.5 (Umeå, Sweden) to create PLS-DA models. The software package provided by Evince is a multivariate image analysis software intended for modelling, thus, it can be used to import and merge all common image and data formats. In the PLS-DA data matrix of CLT, transformed rows are the pixels, i.e., observations under study, and columns are the descriptors, i.e., spectra for the specimen material. PLS-DA was used to extract potential data trends below the mean noise level and to handle pixel observations with missing data [9].

PLS-DA is a machine learning tool for feature selection and classification [27]. In terms of artificial intelligence (AI), this is the equivalent of constructing a machine learning model based on PLS [28]. To perform classification using PLS-DA on the simulated CLT data set, the data set was projected onto the latent structure. This is the machine-learning equivalent of self-prediction. PLS-DA was used as a supervised version of principal component analysis (PCA) in the sense that it achieves dimensionality reduction with classes for feature selection [29]. PCA was used as the typical starting point in multivariate data analysis [30] to access fibre alignment and knot type, i.e., dead vs. sound. Constructed PLS-DA models were used as a supervised pattern-recognition technique to classify CLT specimen features into predefined classes. MIA was used to visually display of results [31]. The data matrix was scaled to unit variance as generally recommended [30].

PLS-DA predictive modelling is a technique to process and solve nonlinear classification problems. PLS started with dimension reduction followed by development of prediction models, i.e., discriminant analysis. PLS-DA exploits the covariance [32]. PLS-DA is a modelling technique for dimension reduction and discrimination based on conventional PLS regression; however, class membership was predicted by the model [33]. PLS-DA finds latent variables in the descriptor space that have a maximum covariance with the predictor variables [34]. Pixel-based models of CLT were created where each pixel was considered as an observation point in space. The PLS-DA models' pixels were predicted, and classification pixels were generated.

3. Results and Discussion

3.1. Rationale for Proposed Methodology to Assess Cross-Laminated Timber. Scheepers et al. [35] confirmed that wood features affecting stiffness can be identified and visualised using multivariate models based on NIR surface measurement data. In a more recent study, Sciuto et al. [36] investigated surface material properties of stone masonry utilising only surface data. Measurements were based on pixel-level matrix data from a hyperspectral push broom system, surface point measurements from a portable NIR probe, and a portable X-ray fluorescence spectrometer to collect point-wise surface data. Specifically, data matrix pertaining to the whole surface was populated with multi-spectrum pixel image data. In selected regions on the surface, measurements with a higher level of detail were performed to improve spatial resolution and extend the wavelength band through a sensor-fusion approach [36].

This study pertaining to CLT is founded on a similar principle and is based on measurements from specific regions of the specimen. However, it stands out in that measurements are performed on the surface all the way through the volume of the specimen, utilising both internal and surface features of CLT. This was made possible by

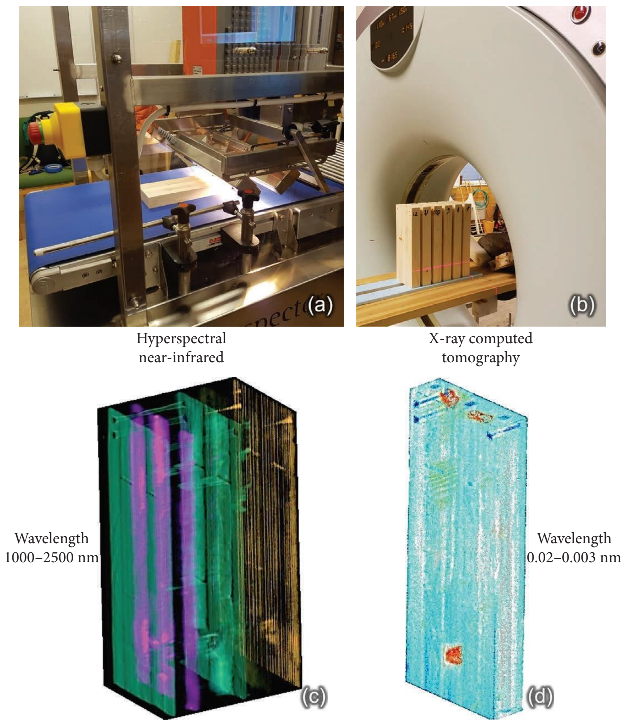

Figure 1: (a) Scanning cross-laminated timber (CLT) specimens with hyperspectral near-infrared (NIR) surface measurements, (b) X-ray computed tomography (CT) surface and internal bulk measurements, (c) projection of surface NIR data with layers in the cube representing different spectral bands, and (d) density of specimen volume from X-ray.

correlating high spatial resolution NIR surface spectral data with X-ray data. This fusion of techniques essentially expands the accessible wavelength range to study CLT, as X-rays have shorter wavelengths than NIR. The distinction of this study is in utilising both the internal and surface material features of CLT. The following sections offer analysis of the results and discuss whether a fusion approach based on NIR and X-ray measurements is feasible to assess CLT panels.

3.2. Principal Component Analysis and Partial Least Squares Discriminant Analysis. With the aid of PCA based on NIR data, descriptive models were developed to project the entire data set onto different subspaces to find trends of correlations. The models identified clusters of materials with the same characteristics based on their spectral signatures. The first component of PCA contour plots obtained in this study distinguished between different fibre alignments, represented as longitudinal 0° layers and transverse 90° layers of CLT specimens in Figure 2. These contour plots visualised the spatial resolution of specific wood anatomical features in the first and second components of CLT. Knots result in interruption of both continuity and orientation of fibres. The second component of the PCA contour plot took this a step further by separating knots from clear wood (Figure 2).

PLS-DA, based on the classes "knot" and "clear wood," predicted knots in an external test set composed of CLT panels. It is worth noting that this test data set was not included in the model's training; as such, it acts as an external validation of the model's effectiveness. The predicted knot can be seen in Figure 3, where the PLS-DA scatter plot shows that clear wood is negatively correlated with the knot cluster.

The PLS-DA model based on NIR can be trained to predict different types of knots within a CLT specimen volume when X-ray data are correlated with the model. This is useful to enhance the detection of wood features hidden below the CLT surface. By combining NIR and X-ray measurements, the spectral wavelength range of the analysis is extended, which facilitates the detection of a broader range of material features. Measuring a small region in high detail and correlating it to the whole of a specimen's bulk volume invariably extends the model's ability to identify correlated material features. In this case, NIR provides an increased level of regional spatial detail as opposed to the overall volume context provided by X-ray.

The PCA contour plot separates knots from clear wood in a specimen bulk volume. It also differentiates between dead and sound knots, with the former appearing dark blue and the latter, red (Figure 4(b)). Dead and sound knots are challenging to differentiate when using only X-ray data because the primary difference between the two types is chemical composition. The chemical composition of knots differs from that of clear wood [37]. In general, depending on the soundness of a knot, colour varies; dead knots appear darker overall [38].

An examination of the PCA scatter plot revealed that the knot cluster was separate from the rest of the specimen cluster, indicating opposite characteristics. In the PLS-DA scatter plot, the knot cluster separates in the first and second components. A single CLT specimen represents millions of values and was sufficient to train the model to identify material features in the training specimen as well as other specimens. The CLT specimens were composed of different wood pieces glued together in a longitudinal and transversely stacked arrangement, increasing the odds that more material features are captured. In general, it is good practice to train the PLS-DA model on several specimens. It is also essential to have an experimental design that captures as many wood features as possible during the model training phase to ensure realistic and robust prediction in real-world situations.

The PLS-DA predictability for the first and second components regarding the three models, namely, X-ray, NIR, and NIR correlated with X-ray, is summarised in Table 1.

3.3. Implications. A multipurpose imaging system has the potential to be used on production lines in real time. As such, the image-based technology assessment proposed in this study can be extended to the product development of CLT. It has been demonstrated that the NIR model could identify features of CLT specimens passing along a conveyor belt in real time. This proposition is consistent with other research fields which also propose the use of NIR as a potential tool for online process control in industrial applications [39].

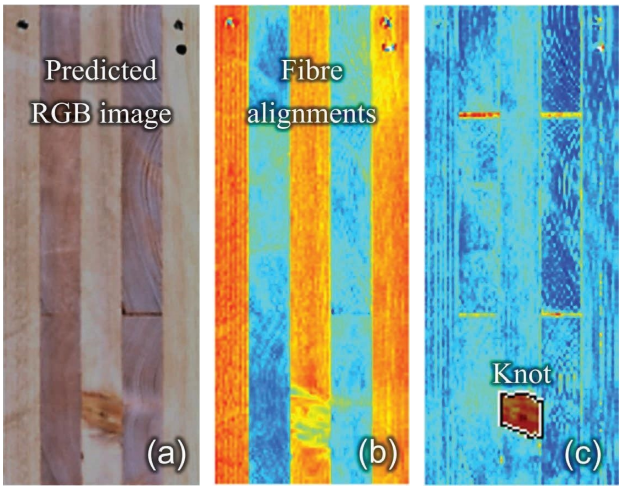

Figure 2: (a) Predicted RGB image; (b) the first principal component analysis (PCA) contour plot component distinguished longitudinal 0° and transverse 90° layers in cross-laminated timber (CLT); and (c) the second PCA contour plot component determined a knot.

Combining NIR with X-ray imaging can enhance the ability of predictive models to identify material features. With additional research, this strategy has the potential for use in an automatic final quality control system to assess whether the CLT manufacturing process meets expectations. NIR and X-ray could also potentially provide the necessary material-passport certification information regarding chemical and physical properties for such CLT. The evaluation of acquired data should not be limited to variables that describe the material's structure alone but also include those capable of predicting mechanical properties of the finalised product.

The continuous production of CLT panels involves systems that transform a considerable amount of raw material into certified products. With further research, such systems could potentially benefit from the integration of a feedback loop into the process-adaptive process control. This will facilitate the instant identification and resolution of technical issues and the continuous monitoring of product characteristics. Such actions may involve accessing parameters related to adhesive bond line quality, moisture content variance, drying defects, milling defects, and material misalignments to deliver thorough process control of the finalised CLT. To ensure CLT panels meet consistent certification requirements, further research to develop and implement nondestructive monitoring technologies for the industry is essential. Image-based systems based on NIR and X-ray, like the one discussed in this study, are paving the way for production-ready systems that can identify problems and measure material properties in real-time quality control systems.

Beyond the timber industry, combinations of NIR and visible-spectrum cameras have been used to monitor polymer films at a macroscopic scale to identify localised defects that are related to the material's mechanical properties [40]. Another study on predicting tensile properties in

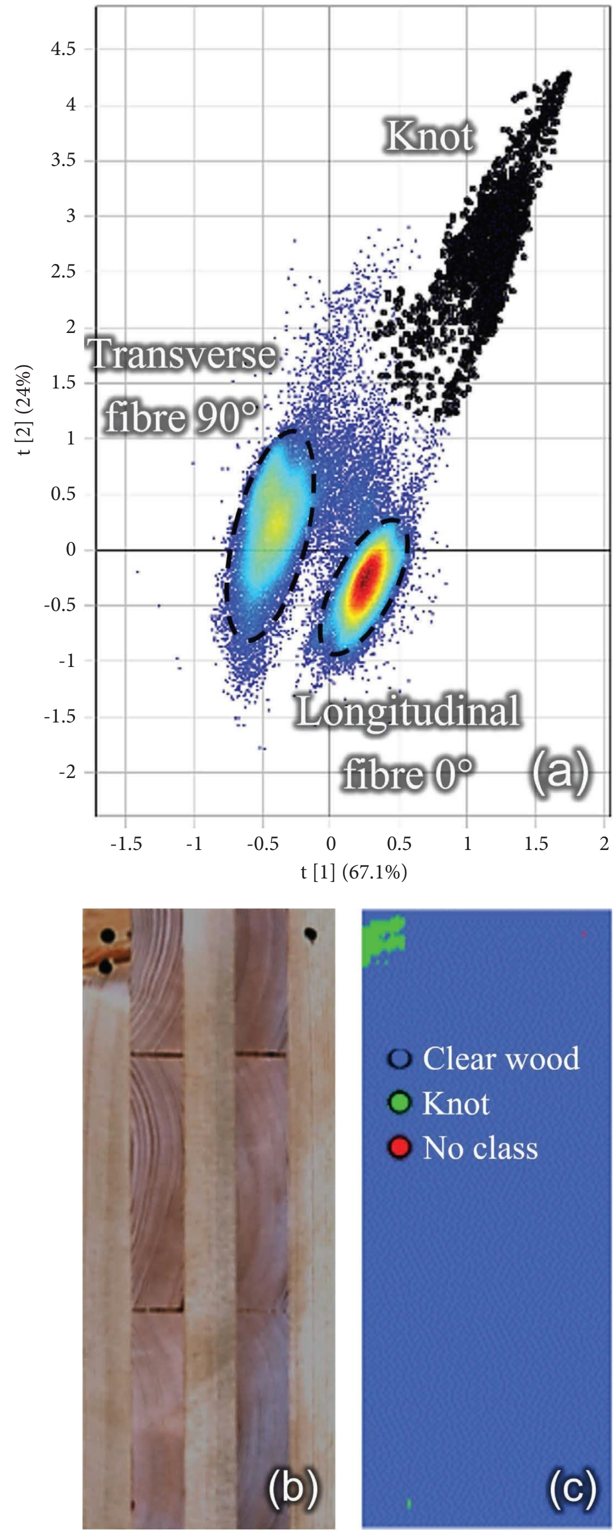

Figure 3: (a) Partial least squares discriminant analysis (PLS-DA) model scatter plot shows that the knot is separated from clear wood and transverse layers are negatively correlated to longitudinal layers, (b) predicted RGB image, and (c) a predicted knot.

film biopolymers also proposed using NIR spectroscopy as a predictor for nondestructive assessment of the film's mechanical properties [41]. X-ray scanning of oversized

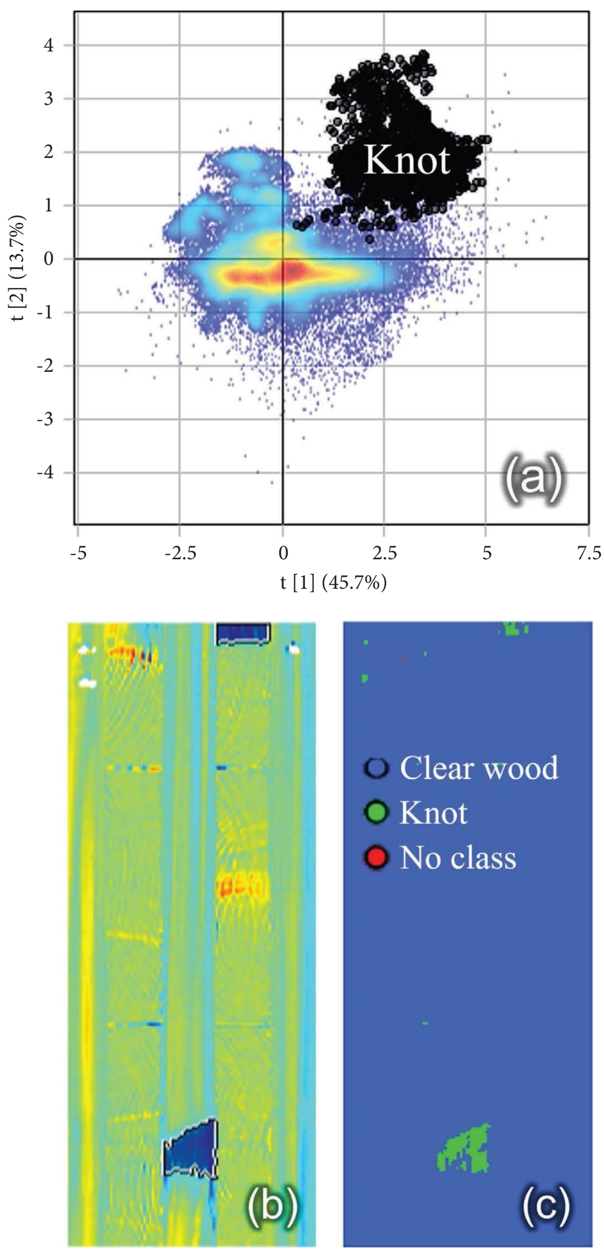

Figure 4: Model based on hyperspectral near-infrared (NIR) surface data and X-ray computed tomography (CT) volume data: (a) knot cluster in black partial least squares discriminant analysis (PLS-DA) scatter plot; (b) contour plot shows knots in a specimen volume; and (c) predicted dead knots.

Table 1: Partial least squares discriminant analysis (PLS-DA) models assessing the predictability of the first and second components based on three different imaged datasets; Near-infrared (NIR), X-ray computed tomography (CT) and NIR correlated with X-ray CT.

PLS-DA	t [1] (%)	t [2] (%)	Sum of t [1] and t [2]
NIR	67.1	24.0	91.1
X-ray CT	27.6	16.5	44.1
NIR correlated with X-ray CT	45.7	13.7	59.4

objects is currently in use in various applications, such as the inspection of shipping containers. Cargo X-ray screening systems have found extensive use in the customs control of containers carrying merchandise. Recently, however, interest has grown in using these scanning systems for more versatile purposes, driving additional technical development [42]. A typical cargo X-ray screening system exists as a drive-through X-ray scanner that allows real-time container validation. The system is modular and designed for integration into existing traffic management systems. A rotating X-ray source for scanning shipping containers has been designed theoretically [43]. However, current cargo transmission X-ray line scanners [44] seem to be of greater relevance to the development of quality control hardware for larger CLT production lines. At this stage, this is a grand vision that requires further research studies to meet industrial requirements. Nevertheless, this technique has the potential as a data-driven assessment tool in industrial processing thanks to its versatility. This research, the first CLT assessment based on pixel-level spectral data, is intended as a screening study to hopefully inspire further research in the field.

4. Conclusions

With the growing market share of cross-laminated timber (CLT) in the construction industry, there is a need for a more comprehensive quality inspection of finished products. There is currently no comprehensive method for continuously monitoring the quality of finished CLT products, so there is a potential to minimise material waste in CLT fabrication. Based on current practices, the crucial process of quality control in CLT fabrication is severely compromised. Considering the economics of CLT, further developments are necessary to implement noncontact and nondestructive inspection. This research presents a strategy to predict material features properties of finished CLT, with the potential to be expanded with further variables to form a comprehensive quality control system.

It was shown that a data-driven machine learning method based on multivariate image analysis (MIA) via partial least squares discriminant analysis (PLS-DA) can be used to classify CLT panel material features.

(1) The model based on near-infrared (NIR) alone could predict material features on the surface of CLT; when combined with X-ray computed tomography (CT), it enhanced the predictive ability of material features in CLT's volume.

(2) MIA conducted on CLT can predict wood features such as fibre alignment and knot type, i.e., dead vs. sound.

(3) Combining NIR and X-ray exploits two different wavelength ranges, enabling useful insights pertaining to material properties for CLT from a broad spectral range.

(4) This proposed method of assessment based on pixel-level spectral data allows for a versatile data-driven detection of material properties of CLT.

Data Availability

The data used to support the findings of this study are included within the article, and assistance in generating similar data is available from the CT WOOD upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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