

Knots searching and location of Chinese Fir (*Cunninghamia lanceolata*(lamb.) hook) constructional lumber from Fujian province, China: using contour fitting and extraction method

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Abstract

This study focuses on studying knots searching and location of Fujian Chinese Fir (FCF) constructional lumber (CL). Combining with the surface characteristics of FCF, a method for locating defects in the knots of FCF CL was developed. Combining with the surface characteristics of FCF CL, searching and locating the knots position at the trough of the profile line. The effect of knot in different position on the modulus of elasticity and the bending strength of FCF CL was studied by mechanical testing machine. This method can be used to calculate the surface defects of lumber quickly and comprehensively, so as to achieve the classification and evaluation of FCF CL according to the standard. This study is of great significance in intelligent detection, efficient production and full utilization of CL, and promotes the safe, stable and green application and development of building materials.

1 Introduction

Modern wood building are mainly represented by light wood structure, glulam structure and wood mixed structure[1]. In recent years, wood structural system have also received extensive attention in the field of scientific research and application in China [2]. Constructional lumber (CL) had been used as a predominant building material due to its higher ratio of weight to strength and renewability [3–5]. There are more and more researches on building materials for modern wood structures, especially lumber, among which the performance of lumber has attracted the most attention[6]. Chinese Fir (*Cunninghamia lanceolata*) (CF) is Taxodiaceae, *Cunninghamia* is a kind of evergreen tree[7]. Fujian Chinese Fir (FCF), with a height of 30m and a DBH of 2.5 ~ 3.0m, is a unique fast-growing timber tree species in China. FCF has straight texture, beautiful color, fine structure, soft material, corrosion resistance and mothproof[8–11]. The knots area of lumber is defined as the branch part of wood during the growth process. During the growth of FCF, there are more live branches or dead branches hidden in the trunk or main branch. Therefore, the FCF CL has many knots defects. Moreover, Fujian Province in China is mostly hilly and mountainous, rugged terrain. The tending of FCF is difficult and the cost of artificial tending is high, which leads to untimely manual pruning. Poor pruning and tending of FCF CL will lead to the problem of many knots[12]. The lumber used in the load-bearing structure is closely related to the position and number of knots[13]. The knots search and location of lumber is the prerequisite for establishing the defect detection, identification and performance evaluation of lumber[14]. Therefore, the research on the knots detection of FCF CL has important significance and application value for the construction application[15].

At present, Some defect detection and grading method still have some problems, such as low detection accuracy, low speed, and serious processing waste. It is of great significance to use Brain-inspired Intelligence technology to replace manual visual inspection of knot location on the surface of lumber. In order to improve the efficiency and accuracy of knots location, and to improve the automation of the detection process, the research of knots location recognition is carried out based on new techniques and algorithms[16]. Several studies proposed a surface defects detection (including knots) method based on the convolutional neural networks (CNNs) for lumbers. However, the input pixel size of the image is

subject to certain restrictions, which affects the detection and recognition of knots for the whole piece of lumber [17–22]. However, in actual factory production, not only the actual size of lumber is large, but also the pixel size of the scanned image required to achieve higher-precision measurement is also larger [23]. The feeding speed of lumber in the processing is required to be high, generally less than 1 m/s [24]. Many algorithms currently proposed cannot meet the above operating speed due to complex calculations[25]. Deep learning requires a large number of samples for training to achieve good generalization[26]. Bruna L. Longo proposed a fully automated algorithm allowed knot detection and positioning on computed tomography (CT) images of Douglas-Fir logs [27]. However, this method is suitable for detecting internal defects of logs, and not suitable for online detection of defects on the surface of lumber. Stephen Wright analyzed Quantifying knots and simulated the mechanical properties of loblolly pine lumber through images, and studied the influence of knots on the mechanical properties of loblolly pine lumber [28]. But there is no discussion and research on lumber anisotropy. K. Kamal proposed a novel approach for classification of wood knot defects for an automated inspection. The proposed technique utilizes gray level co-occurrence matrix and laws texture energy measures as texture feature extractors and feed-forward back-propagation neural network as classifier [29]. However, the knots of the whole piece of lumber are not located, but the marked defects are classified. Ashok Kumar Patel carried out data collection, data preprocessing, feature extraction, feature optimization, model development and performance evaluation [30]. However, the feature extraction of defect on the whole lumber is not carried out. Faster R-CNN with its Region Proposal Network (RPN) was used to model elliptical knots in lumber images [31]. However, the elliptical knot is only one of the knots shape used in the FCF CL, and the location accuracy and integrity of this method need to be further studied.

An algorithm for automatically reconstructing knot geometries within lumber was presented, which was based on non-destructive fibre angle measurements on the surface, exploiting the tracheid effect, and on an estimate of the pith location [32]. However, there is no real-time location of knots on surface of lumber in factory production, and the conclusion is not verified by actual measurement and test. A model using data from a X-ray and grain angle measurements used to perform lumber strength grading was proposed[33]. However, a large number of data samples were needed to calculate modulus of elasticity, static bending stiffness and bending strength. C. Jenkel applied the finite element method to analyze the wood with the characteristics of structural inhomogeneity, and establishes the models of elastic, plastic and macroscopic fracture material on the basis of some geometric data obtained by surface scanning[34]. However, this method was used to represent the mechanical properties of homogeneous wood, free of inhomogeneities, and did not perform real-time location and mechanical performance verification on the actual position of knots of lumber. Markus Lukacevic Proposed a 3D model for knots in sawn timber, simplifying assumption used that knots are shaped like cones (in reality knots are often curved) is a remaining, significant limitation[35]. Although the impact of knot location on the bending stiffness profiles was studied, it did not consider how to quickly obtain the knots position of the whole of lumber in real time. Now, it is urgent to find an method that can search and location knots on lumber, and the algorithm is simple and the cost of hardware requirements is low.

The development of intelligent equipment for detecting wood surface defects based on Brain-inspired Intelligence is of great significance for improving the automation, intelligence level and the utilization rate of wood in the lumber processing industry. This study provides a method for knots location of CL, and lays a foundation for the study of wood grading. The proposed method provide reference for the research and application of modern wood building, improving the intelligent recognition rate, and sufficiency of utilization in lumber defect detection and processing.

2. Materials And Methods

2.1 Materials

The Fujian Chinese Fir trees used in the test were from the Shengsheng Wood Industry Co., Ltd. of Shunchang County, Fujian Province, China, collected from the second generation of Chinese Fir trees in Shunchang County, China. The Trees were 20 ~ 30 years and the diameter at breast height were 180 ~ 250mm. According to the standard ISO 3130:1975 (Wood-Determination of moisture content for physical and mechanical tests)[36], and the moisture content of the tested FCF CL is between 12% ~ 15%. According to the density of the sawn sample of FCF, a number of lumber with different surface knot defects is selected in the several density ranges (0.344 ~ 0.361g/cm³, 0.370 ~ 0.382g/cm³, 0.391 ~ 0.445g/cm³) to test and verify the feasibility of the searching and location method in this study(Fig. 1, Fig. 2, Table 1).

Table 1

The density of Fujian Chinese Fir.

Tree specie	Density (g/cm ³)	Average (g/cm ³)
Fujian Chinese Fir	0.3 g/cm ³ ~ 0.5 g/cm ³	0.40 g/cm ³

2.2. Methods

Combining the surface characteristics of FCF CL. We develop reliable algorithm for knot size. The proposed algorithm is used to process scanning image to realize the location of knots in FCF CL. The logs were sawn into lumber of 40mm×140mm×4000mm, and then the lumber was processed into several small test samples of 17×38×330mm. The machine vision technology was used to scan the image of lumber, and then the algorithm was used to process the collected image to realize the search and location of knots in FCF CL. Finally, the effect of knots on bending resistance of FCF was studied through mechanical testing machine. The research process of knots searching and location of Fujian FCF CL is shown in Fig. 3.

2.2.1 A preliminary searching of gray matrix on surfaces

In the knots searching and location of FCF CL, the upper left corner of lumber is the coordinate origin, the length direction is the x axis, the width direction is the y axis, and the number is FJ-S-G16 as the machine Visually detection samples (Fig. 4).

In the gray image of lumber, the gray value of each pixel is read out, and then the gray value is transformed into the actual position point coordinates of lumber through the proportion of transverse scanning and longitudinal scanning after median filtering[37–39]. In the reading of the gray value of lumber, the gray value in the closed-loop connected domain of 60 value shows a sharp decline, and there are outliers 71 and 75, which may come from the light-colored area that appears inside the knot. Outside the 60-value closed-loop connected domain, there are outliers of 18, 20, 27, and 35. The outliers in this area may come from image digital noise, scanning distortion, light effects, dark stains on the surface of lumber, etc., as shown in Fig. 5. There may also be interference areas with the same gray value of knot outside the detected defects. It is necessary to deal with the above interference, remove outliers, and connect the small outliers areas inside the knot, so as to realize the high-precision location of knots of FCF CL. Therefore, reading out the gray value of the whole lumber in the knots searching and location method is an basic and important step in the processing steps.

2.2.2 The pixel weight calculation on the graph variable edge

The Gaussian filter function based on spatial distribution ensures the preservation of pixel values near the edge, and excludes pixels far away from the edge without affecting the pixel values on the edge[40]. On the basis of retaining the characteristics of knots on the surface of lumber, the spatial filter and distance filter are combined by nonlinear combination of nearby values to sharpen the image, and the problem of cavity in gray image is solved.

$$BF(I)_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p-q\|) G_{\sigma_r}(|I_p - I_q|) I_q \quad (1)$$

Where $BF(I)$ describes the Bilateral Filters, I is the input image, I_p and I_q respectively denotes the image value at pixel position p q , S represents the spatial domain, $G\sigma(x)$ describes the 2-D Gaussian kernel[41–42].

The normalization constant W_p is defined as follows:

$$W_p = w(i,j,k,l) = w_s(i,j,k,l) * w_r(i,j,k,l) \quad (2)$$
$$W_p = \sum_{q \in S} \frac{1}{4\pi^2 \sigma_s^2 \sigma_r^2} \exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma_s^2} - \frac{\|f(i,j) - f(k,l)\|^2}{2\sigma_r^2}\right) \quad (3)$$

Where $w(i,j,k,l)$ describes spatial domain kernel template weight, $w_s(i,j,k,l)$ describes value domain kernel template weight, $w_r(i,j,k,l)$ describes bilateral filter template weight, (i,j) describes the position of the relevant pixel around the target pixel, $f(i,j)$ represents pixel value, (k,l) represents the position of the target pixel, $f(k,l)$ represents the pixel value of the target pixel, σ_s is distance standard deviation of Gaussian function, σ_r is gray standard deviation of Gaussian function[43].

In the detection of the algorithm, the purpose of this algorithm is to eliminate the several cavity areas far away from the knots for the misfits that occur outside the knots of lumber, and can effectively avoid the loss of edge information (Fig. 6 (a)). If the false detection of cavity area cannot be effectively avoided, it will not only affect knots searching and location, but also affect performance evaluation of FCF CL in the later stage. In the area where the gray value of image of the lumber is flat, the point where the pixel change is small, the gray difference is small, the corresponding pixel range is close to 1, and the spatial domain weight plays an important role. At this time, some irrelevant gray change values outside the knot can be processed to avoid misidentification of areas without knot. In the edge area of the knots, the difference in gray between the pixels is large, the pixel range domain weight is large, the spatial domain weight is small, and the edge information can be obtained. The processing effect diagram is shown in Fig. 6 (b).

2.2.3 Spread the connected domain within the knot

Through the reading of the pixel value of a knot, we found that there are some points with higher pixel value in the inner area of the knot, which are caused by the natural characteristics of wood. The situation mentioned above will affect the precise detection of the knots on the surface of FCF. Based on the area filling principle, the connected domain with the internal interference areas within the knots is treated by using spreading domain method.

Based on the area filling method, starting from one pixel $P(x, y)$, $P(x, y)$ spreads in eight surrounding vector directions (Table 2) to achieve the denoising effect[44]. The spreading logic is: if there is no filling, fill it [45]; if it is filled, continue to search for the neighboring pixels in each of the eight vector directions with these eight pixels (Fig. 7), until the enclosed area is completely spread or spread to the predetermined boundary of the knot[46]. This operation provides important help for contour extraction and region separation.

The calculation method of the boundary point vector is as follows:

Table 2

the boundary point vector

the boundary point vector	x coordinate calculation	y coordinate calculation
0	$x = x + 1$	invariant
1	$x = x + 1$	$y = y - 1$
2	invariant	$y = y - 1$
3	$x = x - 1$	$y = y - 1$
4	$x = x - 1$	invariant
5	$x = x - 1$	$y = y + 1$
6	invariant	$y = y + 1$
7	$x = x + 1$	$y = y + 1$

The color and texture characteristics of FCF CL are not uniform. In the detection process, there are often some adjacent closed areas in a knot, which will affect the localization and detection of the knot (Fig. 8(a)). Applying eight-neighbor spreading the connected domain method to fill adjacent pixels, which can spread from a closed area in a knot to other areas, and mark or separate a part of the image of a lumber for processing and analysis. Check whether the current pixel has the original color of the region. If the answer is yes, fill the pixel in the recursive call, and use each adjacent pixel as a new seed; If the answer is no, the current pixel is returned to the caller. In this paper, the spreading the connected domain algorithm is used to extract the central part of the knot, starting from a point (initial point), and traversing nearby pixels. Using this method, the protruding area surrounded by the edge of the knots can be found in the pith of lumber, and the interconnected area surrounded by the knots can be found initially (Fig. 8 (b)). The algorithm successfully solves the problem of individual knots being separated or narrowed, and the calculation is simple and fast.

2.2.4 External expansion and internal contraction

Through the external expansion and internal contraction operations, the basic features of the lumber can be further extracted, and then a higher-level algorithm can be used to identify the knots. The algorithm filter is defined by a planar or non-planar structural element, which is usually moved by pixel on the image and is comparative processing in the corresponding mask. The knot of lumber is expanded externally and then contracted internally. The image of knots maintains the original shape and changes the geometry evenly. In the process of internal contraction, the specified edge point of the internal contraction direction is used as the contraction point[47].

Use vector addition to merge two sets, such as $(a,b)+(c,d)=(a+c,b+d)$. External expansion $X \oplus B$ is the set of all vector sums. The two operands of vector addition come from X and B respectively, and obtain any possible combination[48–49]. Let X and B be the set of two-dimensional integer space P , X is defined by B extension as:

$$X \oplus B = \{p \in \varepsilon^2, p = x + b, x \in X, b \in B\} \quad (4)$$

X is expanded by B is the set of all expanded areas, where B is often called a relative structural element, and the input image is translated by all points of the structural element, and then the union is calculated to obtain the result. The filled area is the result of external expansion, and the filled area includes all the ranges of X . This operation can merge the points around the image into the object, or connect two similar areas in a knot area. Therefore, it is very useful to fill in the cavities in the image, and at the same time, the operation has a filtering effect on the outside of the image of knots[50].

X is defined by B internal contraction as:

$$X \ominus B = \{p \in \varepsilon^2, p + b \in X, \forall b \in B\} \quad (5)$$

Internal contraction of X using B is a set translation of all points in B that are contained in X . The filling area is the result of indentation, and the filling area contains all ranges of X . This operation is a contraction process to shrink the target set, so it can eliminate useless points or small area components in the image, and it can also separate two small connected knots, which has a filtering effect on the image[51].

Let $\check{B}$ be the symmetrical set of B about the reference point, which also becomes the transpose. According to the formula (6), the expansion operation can be used to realize the contraction operation.

$$(X \ominus B)^C = X^C \oplus \check{B}$$

6

Expanded in 8 directions, the image of knots can maintain the original shape. However, when expanding in a single direction, some expansion points are not within the range of the vector table, so there will be a problem that the points that should be expanded cannot be expanded.

There are several ways to solve this problem (the eight directions of the boundary vector are shown in Table 2)

(1) When the vector from this point to the next boundary point is 1, and the expansion direction is 3, if the upper adjacent point (90° direction) or the right adjacent point (0 degree direction) of this point is "1", Extend the points with 1. (2) When the vector from this point to the next boundary point is 3, and the expansion direction is 1, when the lower adjacent point of the left adjacent point of this point is 1, then 1 or the left adjacent point of this point should be expanded. (3) When the vector from this point to the next boundary point is 5 and the expansion direction is 1, if the adjacent point or lower adjacent point of this point is 1, the left or lower adjacent point of 1 is expanded. (4) When the vector from this point to the two boundary points is 7, and the expansion direction is 1, if the adjacent point or lower adjacent point of this point is 1, the right or lower adjacent point of 1 should be expanded. In the process of internal contraction, the key question is how to choose edge points. If there are more than two boundary points on a straight

line, and the vector and the internal contraction direction are the same, only the two end points on the straight line can be contracted on the edge points in the internal contraction direction.

In the process of the contours fitting of knots of CL, if there is a strong light and dark change in the image of knot, that is, there are large changes in the adjacent contours, the knot contours of the point can be extracted. When this algorithm is not applied, the edge error recognition effect is obvious(Fig. 9 (a)). By selecting appropriate structural elements to carry out outward expansion and inward contraction operations on knots of lumber, it can bridge the narrow discontinuities and slender gullies in knot positioning, eliminate small cavities, fill the fracture of contour line, and separate two (more) small connected knots(Fig. 9 (b)).

2.2.5 Searching and localization knots areas on FCF CL surfaces

There is a binary function $z = f(x)$ for the gray scale of lumber, which considers the rate of change of the function in any direction at a certain point. A ray l emitted from the point $P(x, y)$. The ray refers to a directional half-line. Take a point $P(x+\Delta x, y+\Delta y)$ near the point $P(x, y)$ in the l direction, denoted as $|PP| = \rho$. That is $\rho = \sqrt{(\Delta x)^2 + (\Delta y)^2}$ [52]. The directional derivative of the function point P along the direction l (the limit value exists) is:

$$\frac{\partial f}{\partial l} = \lim_{\rho \rightarrow 0} \frac{f(x+\Delta x, y+\Delta y) - f(x, y)}{\rho} \quad (7)$$

The directional derivative is the rate of change of the function z along the half-line.

In the FCF CL, the gray matrix of the knot area and the non-knot area has a large change, the knot has obvious edges, and there are usually multiple gradients on the edge of the knot. If the gradient value appearing at a certain point is large, it means that the light and dark changes of the image at that point are relatively large, and the morphological edge detection will consider that there is an edge.

Known directional derivative formula[53]:

$$\frac{\partial f}{\partial l} = \frac{\partial f}{\partial x} \cos \alpha + \frac{\partial f}{\partial y} \cos \beta = \vec{G} \cdot \vec{l}^0 = |\vec{G}| \cos(\vec{G}, \vec{l}^0) \quad (8)$$

When $\vec{l}^0$ and $\vec{G}$ have the same direction, the direction derivative takes the maximum value $\max(\partial f / \partial l) = |\vec{G}|$.

This study is realized by comparing the changes in the contours of the surface defects of the lumber. Combined with the characteristics of FCF, the gray value change of image of lumber is scanned, and the knot edge contour is fitted and extracted to position knot area of lumber. The pith of the lumber knots of FCF CL is often darker, and the color depth is gradually reduced in the form of the pith gradually radiating

outward, showing a trend of gradient change of the gray value contour. The contour fitting extraction algorithm connects the points with the same gray matrix value of the FCF CL to form a ring line and directly project to the plane to form a horizontal ascent contour line (Fig. 10 (b)), and the ring lines of different heights will not coincide. In the gradient change of the gray value contour line, if there is a trough (groove) (Fig. 10 (b)), search and locate the knot near the area, as shown in Fig. 10.

Based on the introduction in section 2.2.1–2.2.5, the knots searching and location steps for lumber are as follows: through the lumber and background segmentation, determine the coordinate origin of the overall surface of the lumber, and establish the coordinate system of the surface of lumber. The characteristic information of the image is preserved in the spatial domain. With recursive search as the core, the designated color in the Unicom area is replaced from the designated position to eliminate the small outliers area. The target point is merged into the lumber background and expanded to the outside, and the regions with large differences in gray value inside the target knot can be merged, which is convenient for extracting the whole knot. Eliminate the connected boundary of adjacent nodes, contract the boundary inward, separate the knot of different objects that are stuck together, and remove small particle noise[54–56]. According to the type and characteristics (color, lighting, etc.) of FCF CL, use the knot gray value contour algorithm to draw the contour fitting graph, so as to search and locate the knot (Fig. 10 (c)).

3. Results And Discussions

3.1 Evaluation of knots searching and location

The algorithm can distinguish the knots from background of lumber, reduce the edge detection error of knots of FFCF CL, increase the speed of image processing, can overcome the influence of the environment or the captured object, and meet the requirements of high-speed and large-area testing. This study needs to locate the knots in lumber, so as to (a) verify the accuracy of the contour model for searching and locating the current knots, and (b) further study the influence of knots on the lumber. Therefore, this research is to propose an algorithm based on the contour line location of the gray value of lumber, which is used for online nondestructive detecting the position of the knots of lumber, and to provide help for evaluating the quality and grading of the FCF CL. Through this algorithm, the studied knot gray contour change rule also provides reference for the detection of other types of defects. According to the types and characteristics of knots of FCF CL, the gray change curve and the contour fitting diagram of knots using the gray value contour fitting and extraction algorithm, and the knots are searched and located. According to the distribution of knots of lumber, the position of all knots for lumber is counted, as shown in Fig. 11.

A piece of lumber with a size of 1 000×346 mm and 5 knots on the surface was used for knot positioning detection, as shown in Fig. 11 (a). In the contour fitting diagram, three section lines ($x = 74.61\text{mm}$, $x = 185.7\text{mm}$, $x = 433.7\text{mm}$, $y = 50.3\text{mm}$, $y = 101.9\text{mm}$, $y = 141.4\text{mm}$) are made respectively in the transverse and longitudinal directions. The horizontal section line $y = 50.3\text{mm}$ (section line 1) has a trough and a minimum value in the range of $x = 70\text{--}80\text{mm}$ and $x = 200\text{--}210\text{mm}$. Search and locate the knots at this

position to obtain the position coordinates $P_2(x,y)$ and $P_4(x,y)$ of the knots in the lumber. The horizontal section line $y = 101.9\text{mm}$ (section line 3) has a trough within the range of $x = 420\text{--}435\text{mm}$ and a minimum value. Search and locate the knots at this position to obtain the position coordinate $P_5(x,y)$ of the knots in the lumber. The horizontal section line $y = 141.4\text{mm}$ (section line 2) has a trough in the range of $x = 175\text{--}200\text{mm}$, and the minimum value appears. Search and locate the knots at this position to obtain the position coordinate $P_3(x,y)$ of the node in the lumber. The vertical section line $x = 74.6\text{mm}$ (section line 6) has a trough and a minimum value in the range of $x = 40\text{--}60\text{mm}$ and $x = 120\text{--}140\text{mm}$. Search and locate the knots at this position to obtain the position coordinates $P_2(x,y)$ and $P_3(x,y)$ of the node in the lumber. The vertical section line $x = 185.7\text{mm}$ (section line 4) has a trough within the range of $x = 135\text{--}150\text{mm}$ and a minimum value. Search and locate the knot at this position to obtain the position coordinate $P_3(x,y)$ of the node in the lumber. The vertical section line $x = 433.7\text{mm}$ (section line 5) has a trough within the range of $x = 90\text{--}110\text{mm}$ and a minimum value. Search and locate the knot at this position to obtain the position coordinate $P_5(x,y)$ of the node in the lumber. Based on the above methods, the knots of FCF CL can be searched and located.

The obvious change of gray-scale value gradient is found at the knots position, which can accurately locate the knots. Through the steps (the pixel weight calculation on the graph variable edge, spread the connected domain within the knot, external expansion and internal contraction), the lumber can be effectively solved, so as to lay a good foundation for accurate positioning of knots. According to the obtained position information of the knots, the knots distribution of the whole lumber can be further counted, as shown in Table 3. The rBias measured at position x of knots is within 0.61%, and the rRMSE is within 0.49%; The rBias and rRMSE measured at position y of knots are within 0.84% and 0.35%, and the positioning accuracy is relatively high.

Table 3

Evaluation of knots positioning accuracy of Fujian Chinese Fir constructional lumber

Position	x/mm	rBias/%	rRMSE/%	y/mm	rBias/%	rRMSE/%
P_1	65.1	0.61	0.28	109.5	0.42	0.35
P_2	70.3	0.42	0.21	44.8	0.67	0.21
P_3	178.8	0.17	0.21	135.2	0.30	0.28
P_4	193.1	0.16	0.21	45.2	0.84	0.28
P_5	424.6	0.17	0.49	104.5	0.11	0.07

3.2 Statistics of knots areas

Test sample groups FJS1 ~ FJS8, with the size of 1000 × 346 mm, were carried out the experiment of searching and locating the knots, as shown in Table 3, and make statistics on the number and positions of knots of lumber. This research method can quickly, simply and accurately locate and calculate the number and position of knots on the surface of lumber, instead of manual measurement to obtain the information needed for processing and production. Through the observation and application in the production experiment, the growth defects of FCF are mainly knots, which not only affect the wood quality, but also use value and reduce the strength or durability of lumber. Knots are located in different positions of lumber, and their influence on the structural properties of dimension is also different from the application mode of building materials. Therefore, after searching and locating the knots, it is of great significance to statistics of knots and location. The detection experiment of this sample group shows that, as shown in Table 4, the average number of knots in FJS1 ~ FJS8, including 2 end knots, 2 knots on the side (0–1/4 width and 3/4 width - width from the origin) and 4 knots at the center (1/4 width – 3/4 width from the origin). The test results of this sample group show that, as shown in Table 5, the proportion of knots at the center (1/4 width – 3/4 width from the origin) is relatively high, accounting for 53.33%, the proportion of knots on the side (0–1/4 width and 3/4 width - width from the origin) is the second, accounting for 26.67%, and the proportion of knots at the center (1/4 width – 3/4 width from the origin) is 20.00%. The above detection and statistical data show that this method can accurately search and locate knots, which can not only be used as an important basis for the quality evaluation of FCF CL in the later stage. It is also an important step in the production and processing of lumber, breaking the traditional thinking and processing mode of manual visual marking of FCF. Make up for the shortcomings of traditional methods and promote the safe and stable green application and development of building materials.

Table 4

Position and quantity statistics of knots of Fujian Chinese Fir construction lumber

Samples	The sum of knots	End knots(pcs.)	Knots on the side 0-1/4width and 3/4 width - width from the origin (pcs.)	Knots at the center 1/4 width -3/4 width from the origin (pcs.)
FJS1	7	3	1	3
FJS2	5	1	1	3
FJS3	9	2	1	6
FJS4	12	2	6	4
FJS5	5	2	0	3
FJS6	8	2	1	5
FJS7	8	0	3	5
FJS8	6	0	3	3
sum	60	12	16	32
average	7.5	1.5	2	4

Table 5

The proportion statistics of the position and number of knots of Fujian Chinese Fir constructional lumber

Samples	The sum of knots	End knots(pcs.)	Knots on the side 0-1/4width and 3/4 width - width from the origin (pcs.)	Knots at the center 1/4 width - 3/4 width from the origin (pcs.)
FJS1	7	3	1	3
FJS2	5	1	1	3
FJS3	9	2	1	6
FJS4	12	2	6	4
FJS5	5	2	0	3
FJS6	8	2	1	5
FJS7	8	0	3	5
FJS8	6	0	3	3
sum	60	12	16	32
average	7.5	1.5	2	4

3.3 Effect of knots on bending resistance of Fujian Chinese Fir constructional lumber

The mechanical experimental materials were FCF. Using the traditional four-faced sawing method, the lumber is sawn into the size of 40mm×140mm×4000mm. Then the lumber is processed into several small specimens of 17×38×330mm. The specimen is subjected to a three-points bending test with a Instron 3369 micro –computer electronic universal mechanical testing machine.

From the appearance, there are more knots in FCF, and most of them are slipknots, and the number of dead knots is less. The modulus of Elasticity of six groups of FCF with different knots is 6.11 GPa, 6.09 GPa, 6.29 GPa, 6.39 GPa, 6.92 GPa, 6.17 GPa. The bending strength of six groups of FCF with different knots is 84.12 MPa, 111.99 MPa, 107.68 MPa, 105.62 MPa, 99.69 MPa, 92.07 MPa, and the coefficient of variation is 23%, 22%, 21%, 13%, 21%, and it is higher than 15% of the variation coefficient of bending strength stipulated in the code, as shown in Table 6. The results show that the bending strength of lumber is good, and there is a correlation between knots and the bending strength of lumber with knots. The bending strength of lumber with knots decreased.

Table 6

Effect of knots on bending resistance of Fujian Chinese Fir constructional lumber.

Groups	MOE(GPa)	MOR(MPa)
A	6.11 ± 0.87	84.12 ± 7.05
E	6.09 ± 1.78	111.99 ± 25.33
F	6.29 ± 2.27	107.68 ± 16.21
G	6.39 ± 2.51	105.62 ± 21.78
H	6.92 ± 1.71	99.69 ± 12.63
T	6.17 ± 1.54	92.07 ± 19.76

It can be seen from Fig. 7 that when FCL with knots was pressed from the narrow side, the specimen failure occurred at the knots, and the specimen appeared stratification and fracture. After the pressure was removed, the specimen showed obvious deformation. Different knot positions will cause different stress distributions, which will change the elastic modulus and bending strength of lumber. When the knot appears on the edge of the FCF CL, it first breaks in the test of mechanical testing machine, as shown in Figure.12.

Table 7

MOE and MOR decline rates of knotted Fujian Chinese Fir.

Samples	MOE(GPa)	MOR(MPa)
FJ-S-G13	0.9%	33%
FJ-S-F15	2.5%	28%
FJ-S-G16	4.1%	26%

As can be seen from Fig. 13, FCF have good mechanical properties. the mechanical properties of FCF decreased, and the mechanical properties of FCF decreased obviously.

In terms of the failure forms of specimens, the failure of FCF was accompanied by slippage and stratification in addition to the fracture of wood fiber. The shape variable of FCF was more obvious after the pressure was removed, Especially knots on the side.

The bending strength of lumber is mainly affected by knots and other defect factors, especially FCF CL is mainly affected by knots. Machine vision inspection has many advantages. Most mechanical stress grading equipment used today can not detect these defects. However, mechanical strength is related to the distribution of knots. Machine vision inspection and evaluation has many advantages. Most mechanical stress grading equipment used today can not detect these defects. However, mechanical strength is related to the distribution of knots on lumber. The effects of knots of the whole lumber on the strength reducing characteristic were studied to verify that reduces its load bearing capacity. The study on the effects of knots on the strength reducing characteristics of FCF CL has verified that knots will reduce its load bearing capacity.

Based on developed algorithm, the knots of FCF CL are located, and the weak parts of lumber are searched and determined. Through mechanical bending resistance test, MOE (modulus of elasticity) and MOR (modulus of rupture) were determined to study the influence of knots on mechanical properties of FCF CL. As shown in Table 7, knots will reduce the mechanical properties of FCF CL. he modulus of elasticity, and MOE average decline rates of knotted FCF is 2.50%. The bending strength of FCF with knots is good, and there is a significant correlation between knots and the bending strength of CL with knots. MOR average decline rates of knotted FCF is 29.00%. Knots will reduce the bending strength of lumber, especially knots at the edge (FJ-S-G). In the area with knots, the average MOE and MOR of CL are 6.33 GPA and 100.20 MPa respectively. The above research shows that the mechanical properties of FCF CL are gradually reduced by the knots. Knot is the main defect characteristic of FCF CL. Knot is an important factor affecting MOE and MOR of lumber. It lays a foundation for the study of various defects affecting strength or related properties on the surface of lumber.

5. Conclusions

This study focuses on defect searching and location of FCF CL. Combining with the surface characteristics of FCF CL, a suitable method for knots location of FCF CL. The algorithm overcomes the influence of environment or captured object and meets the requirements of large-area lumber testing.

Through this algorithm, the position information of the knots is obtained, and the knots distribution of the whole lumber is further counted. the mechanical properties of FCF CL are evaluate by this nondestructive testing method. The detection of knots based on contour fitting and extraction algorithms can improve the accuracy and effectiveness of grading, thereby improving the sufficiency of wood utilization and applying it to actual production.

Declarations

Credit authorship contribution statement

Min Ji: Methodology, Resources, Experiments, Analysis, Roles/Writing - original draft. Wei Zhang: Methodology, Resources, Analysis, Writing - review & editing. Rui-qi Zhang: Methodology, Validation, Guo-fu Wang: Experiments, Validation. Hu Miao: Experiments, Rui Gao: Validation.

Declaration of Competing Interest

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

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Data availability

The data sets generated during and/or analysed during the current study are available from the corresponding author upon request.

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Figures

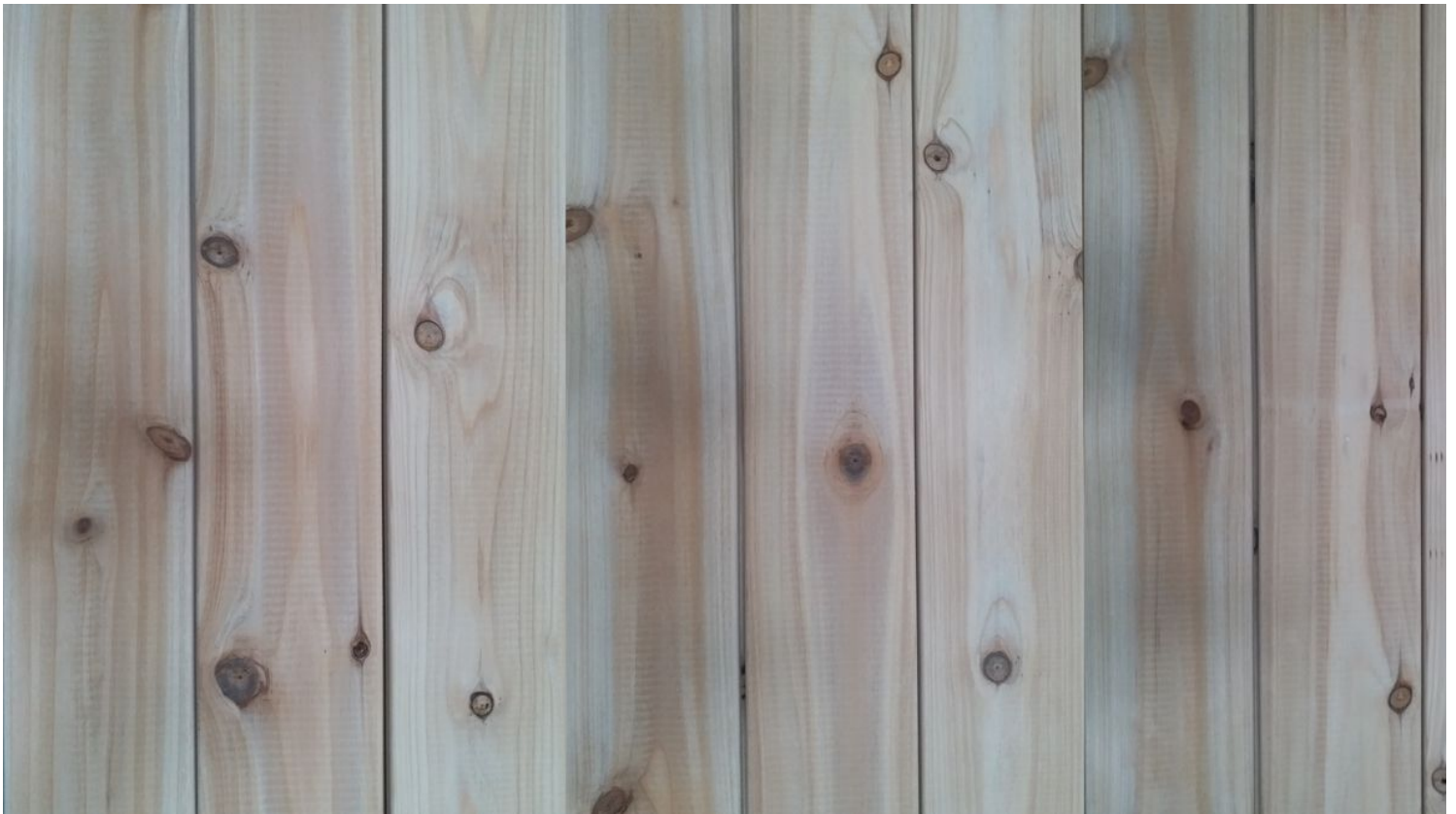


Figure 1

Fujian Chinese Fir constructional lumber

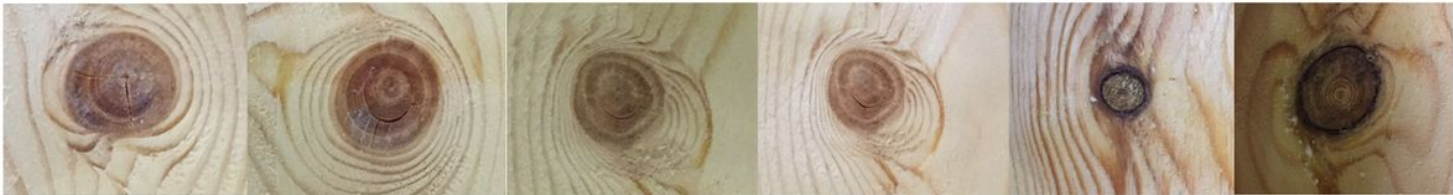


Figure 2
Characteristics of knots of Fujian Chinese Fir constructional lumber

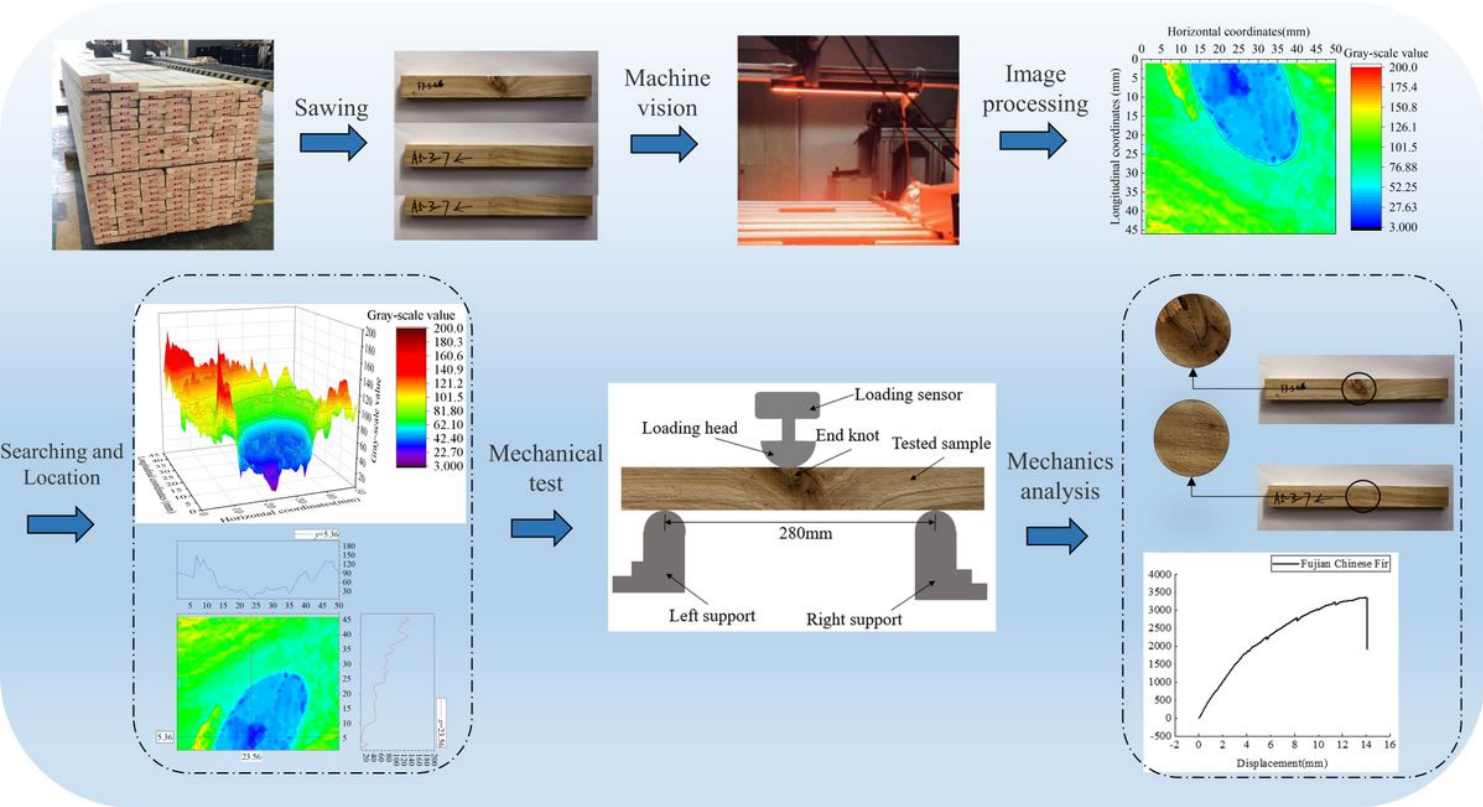


Figure 3
The research process of knots searching and location of FCF CL



Figure 4

Knot of FJ-S-G16 Fujian Chinese Fir constructional lumber

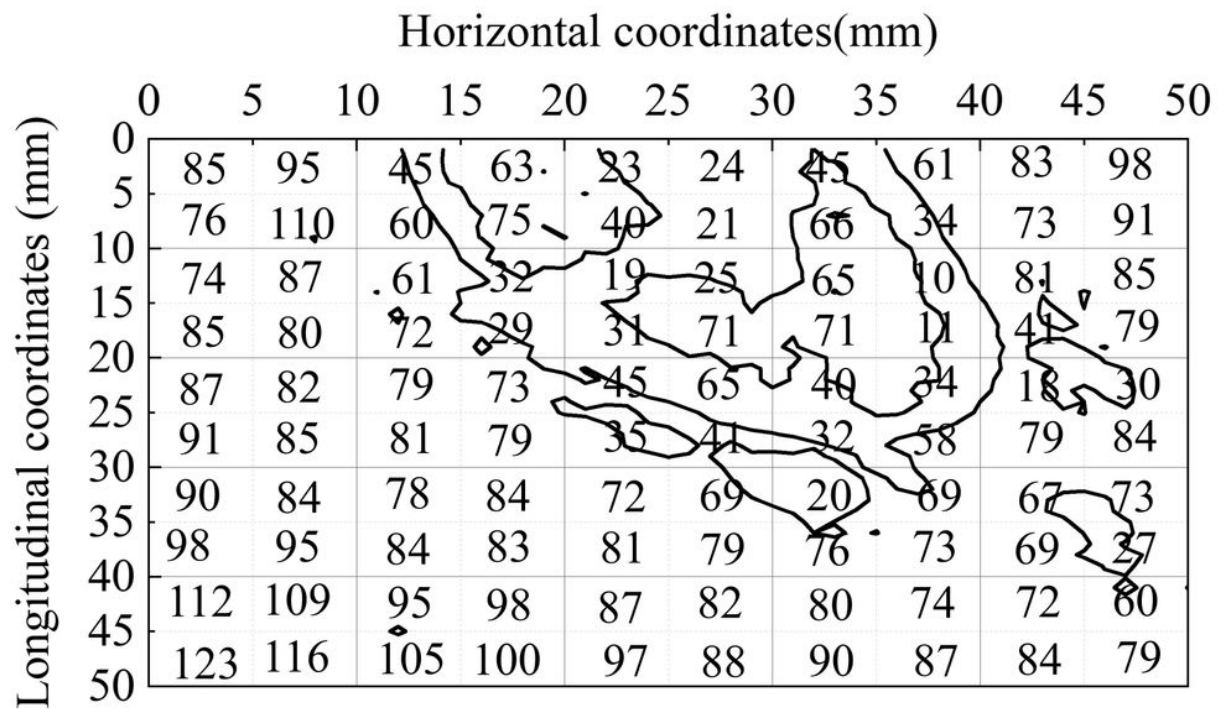


Figure 5

Gray-scale value of Knot for Fujian Chinese Fir constructional lumber

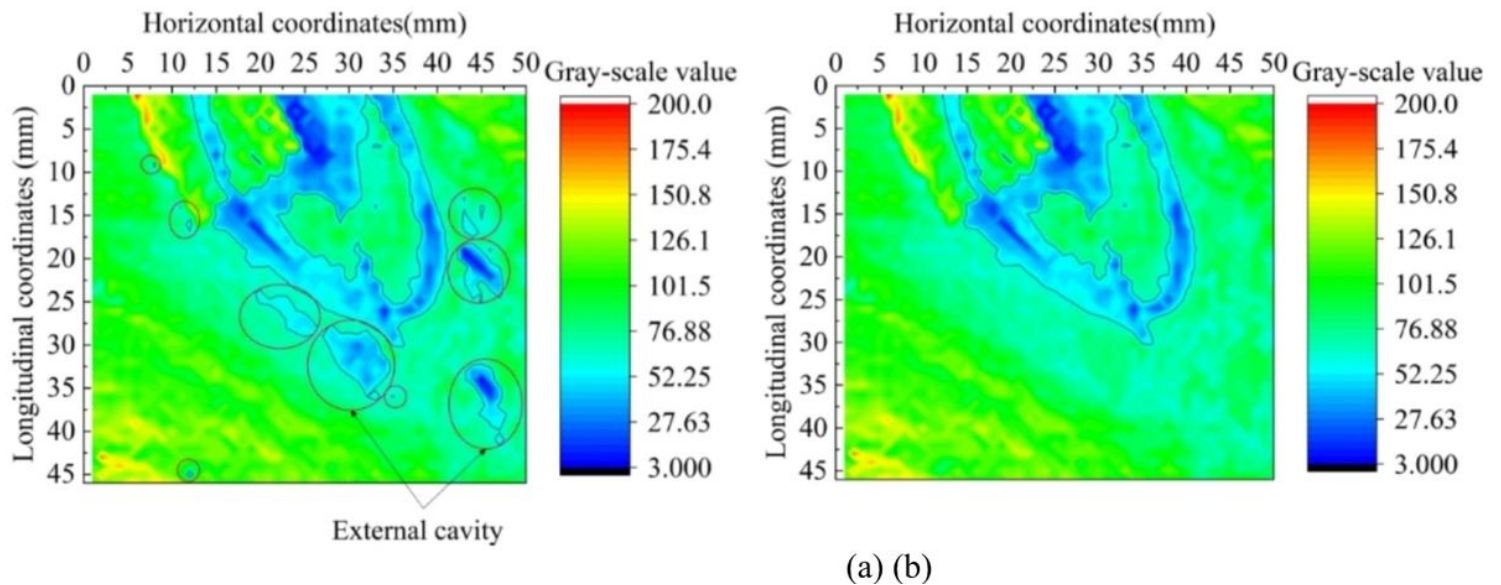


Figure 6

The pixel weight calculation on the graph variable edge (a) Knot searching of

Fujian Chinese Fir constructional lumber before external cavity removal (b) location after external cavity removal

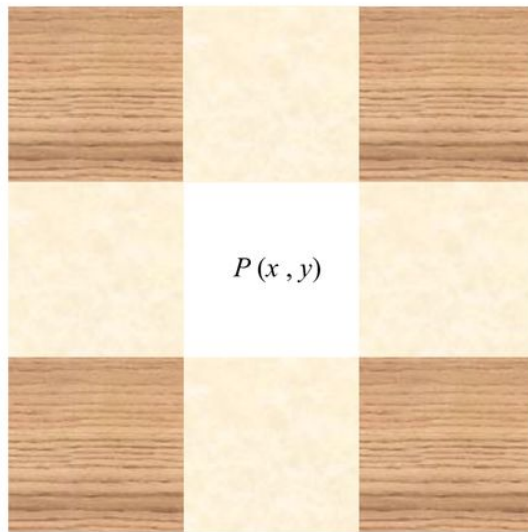


Figure 7

Eight neighborhood point search

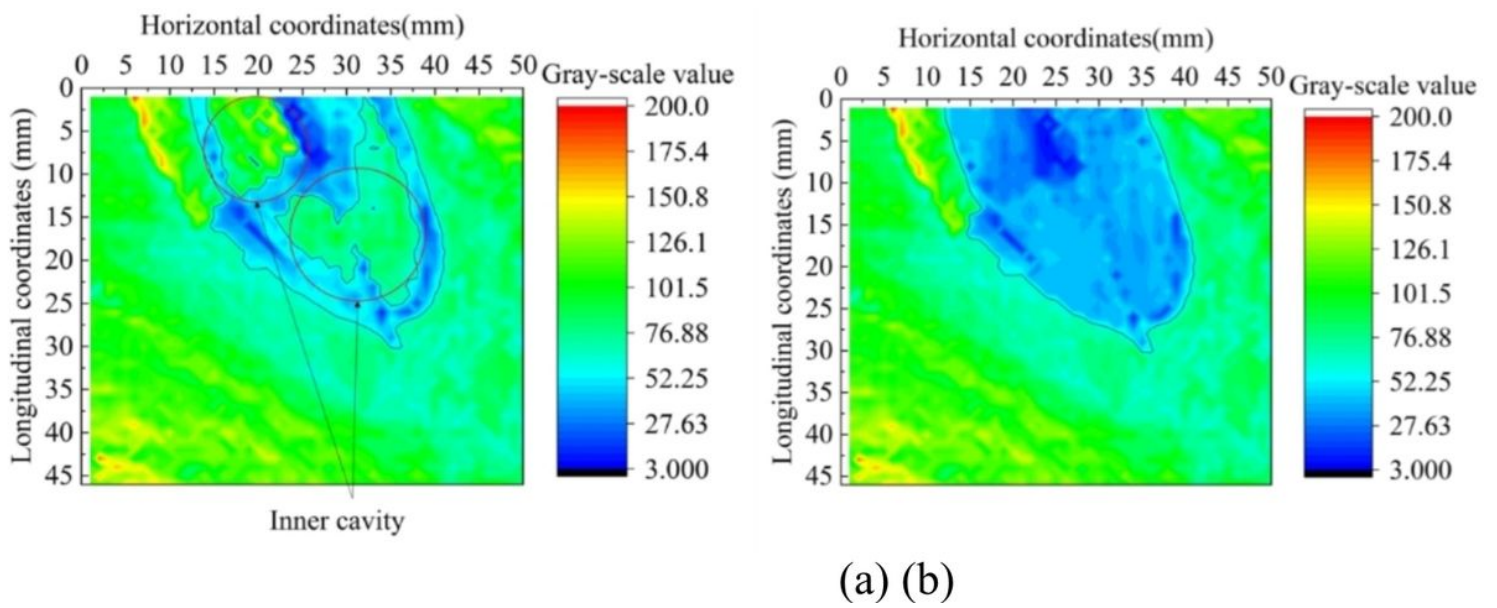


Figure 8

Spread the connected domain within the knot (a) knots location of FCF CL before inner cavity removal (b) location after inner cavity removal

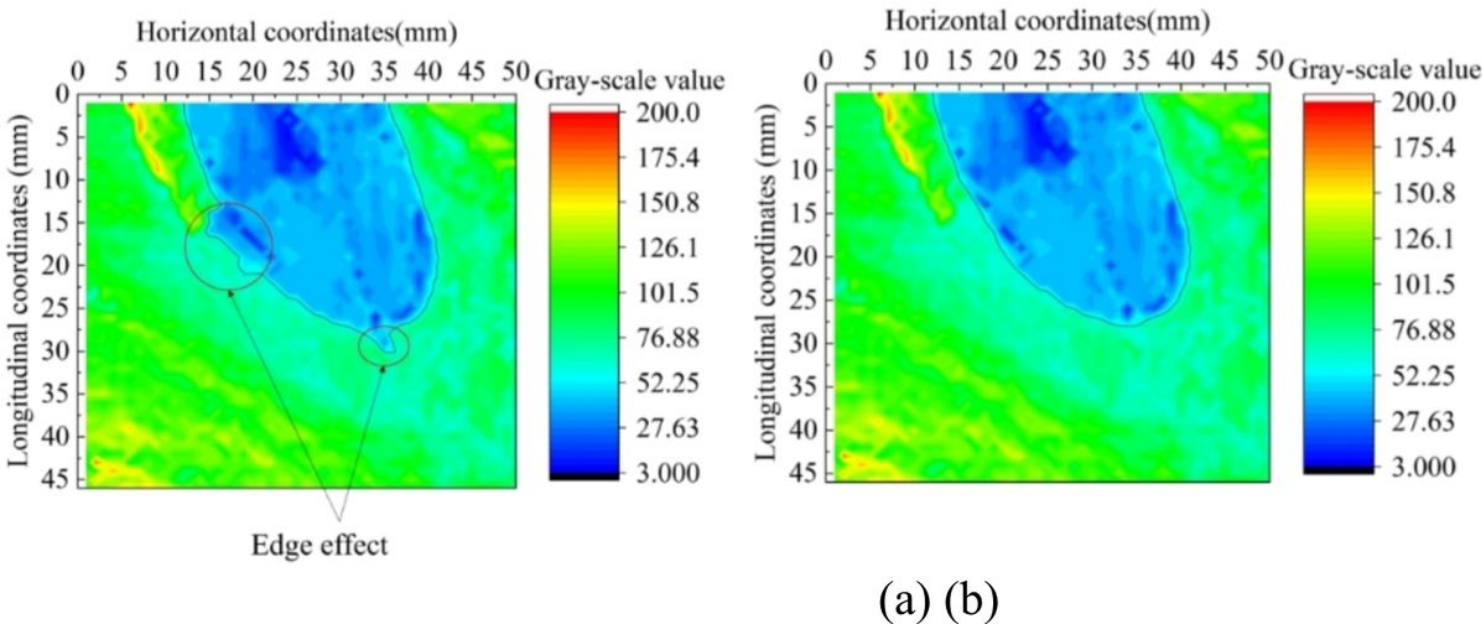


Figure 9

Spread the connected domain within the knot (a) knots location of lumber before inner cavity removal (b) location after inner cavity removal

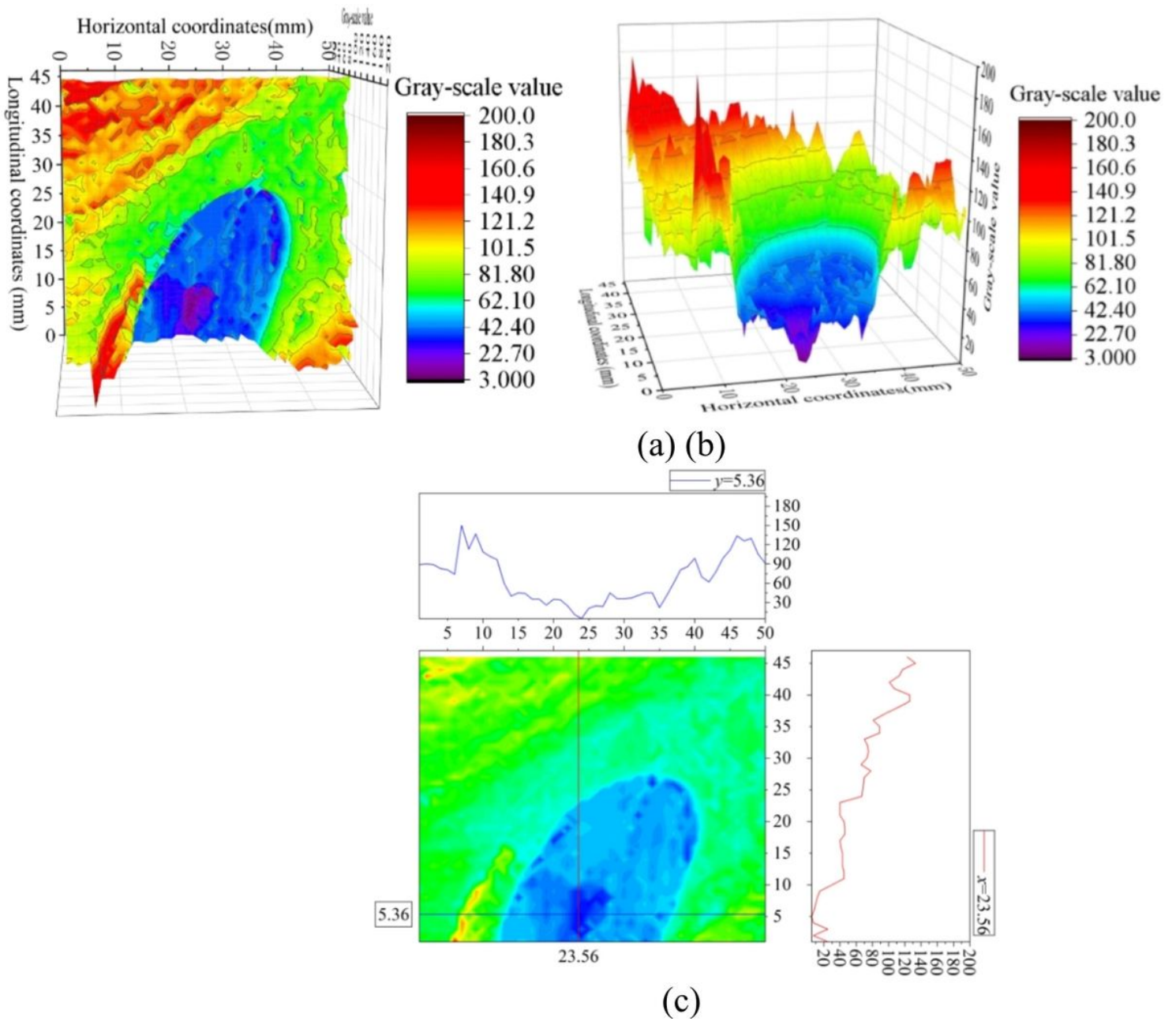
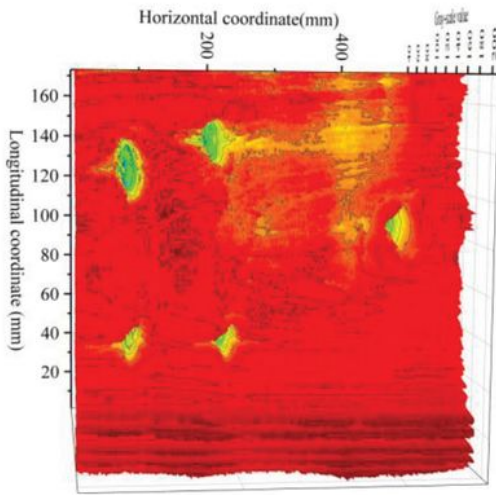


Figure 10

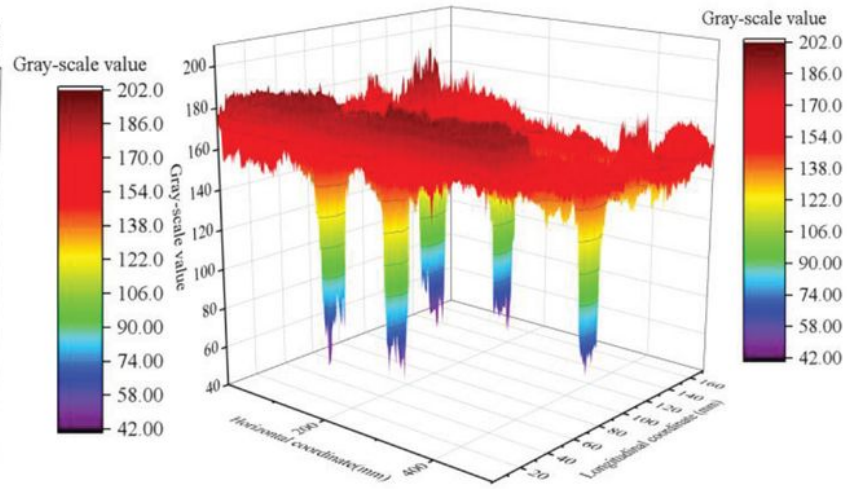
Researching and Localization of knots areas on structural lumber surfaces (a) projection of 3D mapping curve (b) contour 3D mapping curve (c) Contour sectional graph of knot



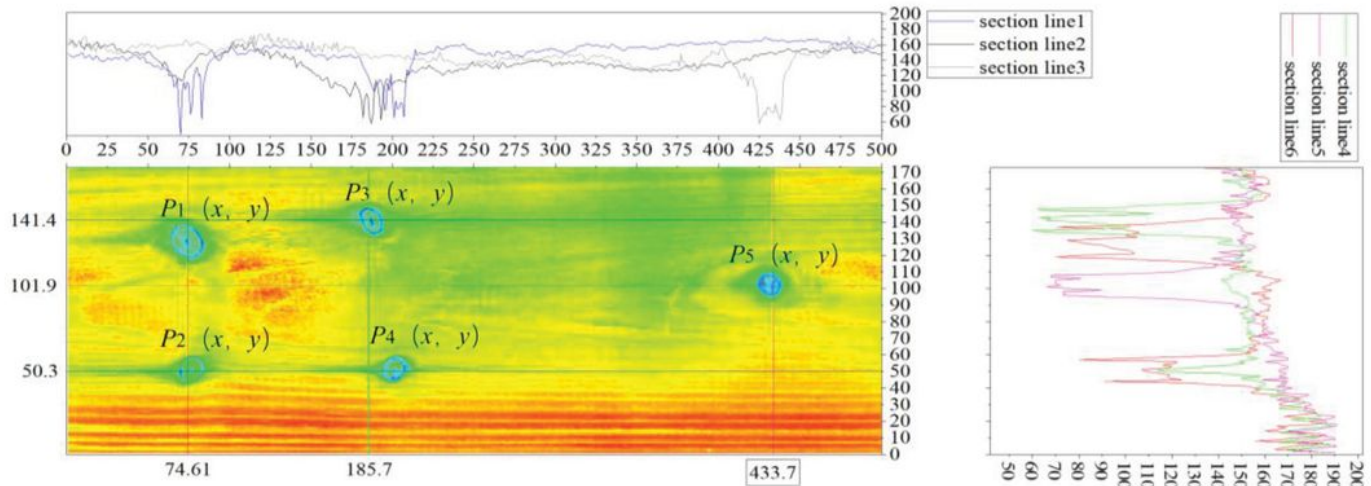
(a)



(b)



(c)



(d)

Figure 11

Researching and Localization of knots areas on structural lumber surfaces (a) FCF CL (b) contour 3D mapping curve (c) projection of 3D mapping curve (d) Contour sectional graph of knot

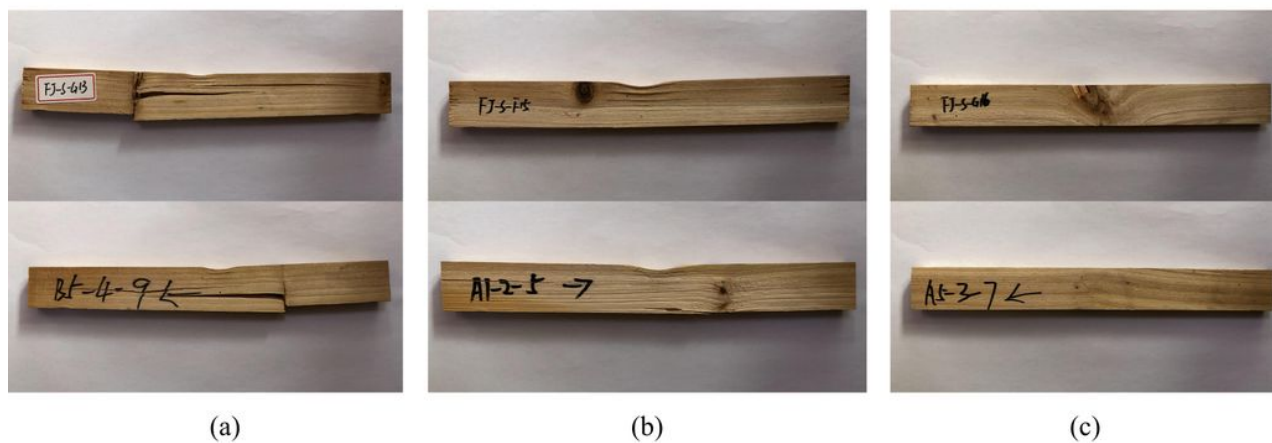


Figure 12

Cracks in the final failure of Fujian Chinese Fir (with knots) (a) test sample of Fujian Chinese Fir:FJ-S-G13 (b) test sample of Fujian Chinese Fir:FJ-S-G15 (c) test sample of Fujian Chinese Fir:FJ-S-G16

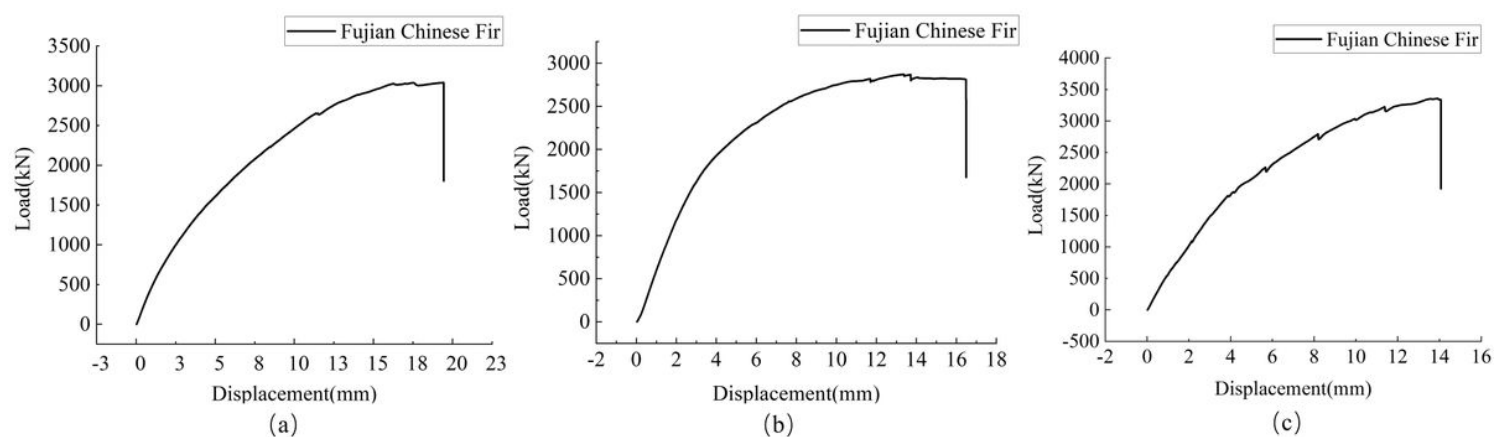


Figure 13

Displacement - load curves of several typical European Spruce and Chinese Fir with knots (the size of the knots is d (diameter)). (a) FJ-S-G13, (b) FJ-S-F15, (c) FJ-S-G15

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