ULTRASOUND PALLET PART EVALUATOR/GRADER AND CANT SCANNER

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ABSTRACT

Sorting and grading of wooden pallet parts are key factors for manufacturing quality and durable pallets. The feasibility of ultrasonic scanning for defect detection and classification has been examined in this report. Defects, such as sound and unsound knots, decay, bark pockets, wane, and holes were scanned on both red oak *(Quercus rubra,* L.) and yellow-poplar *(Liriodendron tulipifera,* L.) pallet materials. Scanning was conducted by two pressure-contact rolling transducers in a pitch-catch arrangement. Pallet parts, such as deckboards, stringers, and cants were fed through the transducers, and data were collected, stored, and processed with software written in the LabView™ environment. Defects were characterized on the basis of time of flight, pulse energy, and pulse duration of the received ultrasonic signals. Significant losses of energies were observed through these defects. Time of flight is less sensitive to defects compared to other parameters. This relative change of parameter values, with respect to values for clear wood, can be used to locate, identify, and quantify various pallet part degrades. Two-dimensional images were constructed using multi-line scanning data. The reconstructed images are able to show the position and surface area of the defects. Defects were classified using a multi-layer perceptron (MLP), a probabilistic neural network (PNN), and a K-nearest neighbor (KNN) classifier. Defective wood was classified quite clearly and accurately by all of these networks with high recognition rates. Decay has a higher recognition rate than the other defects. Wane and holes were readily confused owing to their common loss of transducer contact. The MLP were found to be more efficient for classifying these defects. Results demonstrate that real-time, on-line inspection and classification of defects in wooden pallet parts are possible by ultrasonic scanning.

INTRODUCTION

Approximately forty percent of the hardwoods produced in the United States are used for manufacturing pallets. Wooden pallets are the largest single use of sawn hardwoods, consuming 4.5 billion board feet of lumber for manufacturing 400 million pallets annually. Pallets are integral to the US transportation infrastructure, as almost all products spend a part of their life on a pallet, either as component parts or following final assembly. Typically, a wooden pallet consists of two parts-stingers, the structural center members that support the load, and deckboards-the top and bottom members that provide dimensional stability and product placement. There are many types of pallet designs based on the size, number, and position of the stringers and deckboards. Usually, pallet parts are produced from the low quality lumber or from the center cant materials of logs. These cants have a high percentage of defects, and therefore have less market value for other solid wood products.

High quality pallet parts produce higher grade and longer lasting pallets with increased material handling safety, and permit multiple trips before repair, recycling or remanufacturing. The presorting and optimized sawing of cants can reduce processing cost and will produce higher grade pallet parts. Manual grading and sorting of pallet parts is a slow and inaccurate process, which depends on the individual skill of the grader. Moreover, the presence, location, and extent of defects in pallet parts are often difficult to determine accurately, making manual grading complicated. An automated, nondestructive machine would be very useful for pallet industry for the sorting and grading of these pallet parts.

Detection and classification of defects in a pallet part is a challenging and complex task. Several nondestructive methods have been employed for detecting defects in wood, including X-ray, microwave, dielectric, optical, acoustic/ultrasonic, and laser (Szymani and McDonald 1981). Each of these methods has distinct advantages and limitations. Ultrasonic scanning has many advantages-through transmission (able to scan inside of the board/wood), faster, nondestructive and non-hazardous. The most common defects found in wood or pallet parts are sound and unsound knots, cross grain, decay, bark pockets, splits, holes, and wane. Many researchers have investigated the feasibility of using ultrasound for detecting these defects in wood (McDonald 1980, Schmoldt et al. 1994, 1997, Ross et al. 1992, Fuller et al. 1996, Niemz et al. 1999, Raczkowski et al. 1999, Karsulovic et al. 2000).

The most common way of detecting defects using ultrasound is the measurement of transmission time through clear and defective wood. The measurement of transmission time is useful when there is only a single type of defect in a board. Some defect types may not respond well to the transmission time, but may respond to the other ultrasonic parameters, e.g., peak amplitude, centroid time, frequency domain energy, etc. Recent studies showed that the frequency domain analysis (Halabe et al. 1994, 1996) and energy loss (Brashaw et al. 2000, Kabir et al. 2002) parameters are able to detect defects efficiently in wood.

The classification and recognition of defect types in a single sample is very difficult and complicated using any automated scanning system. The changes in the measurement parameters for many of these defects are similar, making classification systems difficult. Once we are able to detect, locate, and classify defects, grading of pallet parts is possible using established grading rules.

MATERIALS AND METHODS

The scanning equipment was provided by the former Ultrasonic Group, Forest Products Division of Perceptron Inc. The system consists of in-feed and out-feed roll beds, two pinch rollers for part movement, and two rolling transducers which are mounted in an ultrasonic ring. The bottom transducer transmits ultrasonic pulses and the top transducer receives those pulses. Pallet parts move through the system, lying on a face, and ultrasonic signals propagate through the part's thickness. The necessary electronics and software to control material movement, signal generation, data collection, and analysis were supplied by Perceptron. The desired scanning resolution can be achieved by controlling roller speed and the number of pulses generated per second. All measurements were carried out at 120 kHz transmitting frequency and received signals were sampled at 500 kHz.

Deckboards, stringers, and cants were collected from local sawmills for both yellow-poplar *(Liriodendron tulipifera,* L.) and red oak *(Quercus rubra,* L.). They were fresh cut and unplaned, and were kept immediately in cold storage to reduce their drying rate and to keep their moisture content above fiber saturation point. Twenty-five deckboards, eighteen stringers, and eight cants were scanned for each species. Each sample contains both clear and defective wood and the scanning was conducted in two ways. First, a line was marked on the board through a defect of interest and scanning was done along this line. Second, six scan lines were marked longitudinally along the face of each sample 1.27 cm apart across the width of the board, and scanning was performed along these six lines. These multi-line scans were used to characterize the entire deckboard and to construct a 2-D image.

ULTRASONIC VARIABLES

The ultrasonic scanning involves measurement of many parameters-three for time-of flight, two for ultrasound pulse energy, one using ultrasound pulse duration, and peak frequency. The wave energy of the received signal can be expressed as the time integral of the voltage:

$$E = \int v^2(t)dt \tag{1}$$

Parameters include pulse length (PL), time of flight-centroid (TOF-centroid), time of flight- energy (TOF-energy), time of flight-amplitude (TOF-amplitude), energy value, energy/pulse value, and peak frequency. The energy value (EV) or loss is expressed as the ratio of the energy received by the receiving transducer to the energy input to the transmitting transducer, and is given by:

$$EV(d\dot{B}) = 10\log\left[\frac{E_r}{E_t}\right] - G \qquad (2)$$

where E_r is the energy received by the receiving transducer, Et is the energy input to the transmitting transducer, and G is the receiver gain. This parameter is normally expressed in decibels (dB) and by convention in logarithmic (and hence a negative number) with lower signal ratios being more negative. The pulse length parameter is derived from the integral expression above. This is defined as 1.25 times the time required for the received wave energy to rise from 10 percent to 90 percent of its total energy and is expressed in microseconds. These two parameters, energy value and pulse length can be combined to provide more defect resolution, known as energy/pulse value (EPV). Again, because of the wide range of energy levels, EPV is also expressed on a logarithmic scale (dB)

Time of flight (TOF) measurement can be associated with the energy, amplitude, or centroid of the signal. TOF-energy is calculated as the time at which the energy integral crosses a threshold value-as a percentage of the final value. If the threshold value is, for instance, 40 percent, then TOF-energy is simply the time at which the integral value reaches 40 percent of the final value. Similarly, TOF-amplitude is the time at which the amplitude of the signal first reaches, for instance, 40 percent of the maximum amplitude. TOF-centroid is the time to the centroid of the time waveform, which is based on the ratio of the first- and zeroth order moments.

CLASSIFICATION OF DEFECTS

Two artificial neural networks, multi-layer perceptron network (MLP) and probabilistic neural network (PNN), and K-nearest neighbor (KNN) were used to classify defects. Theory and details of these classification methods can be found in Duda and Hart (1973), Specht (1990), Gonzales and Woods (1992) and Tiitta et al. (2001). The classification methods were tested and compared by using training and testing for each set of data. For classification with MLP and PNN, we created 10 groups of data using energy, pulse length, TOF-a, TOF-e, TOF-c, EV, EPV and peak frequency. Each set of data contains all type of defects. Initially, each network was trained with nine sets of data and the trained network was tested with 10th set of data. This method of training and testing was done ten times for 10 sets of data.

Artificial neural network (ANN) is one of the most commonly used network for pattern classification. The ANN follows the behavior of the brain for pattern recognition, reorganization, and learning. Multi-layer Perceptron (MLP) network, which consists of a large number of simple interconnected structurally identical processing elements, was used for training and testing. The MLP network basically is a layer of neurons connected so that the output of every neuron in one layer feeds into the input of every neuron in the next layer. The inputs of each neuron are multiplied by its weights and then summed the result into a single value. The neural network weights were adjusted using back-propagation supervised training to get the output very close ‘to the known target. Successive repetitions of adjustment were made to the weights until the difference between the input and the target was smaller with each iteration. The output of each neuron can be calculated after the value passes through a non-linear sigmoid function. An MLP network with 2 hidden layers is designed for our classification purpose. The number of neurons in the hidden layers are 16 and 10, respectively.

Probabilistic Neural Networks (PNN) are a class of neural networks, which combine some of the best attributes of statistical pattern recognition and feed-forward neural networks. PNNs feature very fast training times and produces outputs with Bayes posterior probabilities. The PNN is interpreted as a function, which approximates the probability density of the underlying examples’ distribution. K-nearest neighbor classifier is a non-parametric classifier. The training set for each class represents a class and the unknown pattern from the testing set is classified by finding the nearest neighbors from the set of training patterns. Statistically, more reliable results can be achieved by using more than one nearest neighbor. The traditional k-nearest neighbor classifier finds the k nearest neighbors based on some distance metric by finding the distance of the target data point from the training data set and finding the class from those nearest neighbors by some voting mechanism. For the verification of the classifier, we used the leave-one-out method, in which a classifier is constructed with all sample data except one and the excepted data is used to test the classifier. The leave-one-out method repeats this process for every sample data.

RESULTS AND DISCUSSIONS

The collected ultrasound data in this experiment mostly was based on the time of flight, energy loss and peak frequency measurements through clear and defective wood. The energy value (EV), time of flight-centroid (TOF-c) and peak frequency (PF) of clear and defective wood of oak and yellow-poplar deckboards and stringers are shown in Table 1. Defective wood, such as sound and unsound knots, decay, bark pockets and holes can be clearly distinguished and identified from clear wood based on the values of different parameters. The energy value parameter was found to be more sensitive for defect detection compared to TOF-c and PF. The TOF-c increases slightly in the region of sound knots both for deckboards and stringers. The changes of the EV relative to the clear wood value for unsound knots, decay, and bark pockets of oak deckboards are similar. These three defects have common ultrasonic signatures and can be considered as unsound defects. Decay and holes exhibited a higher PF, making this parameter can useful for distinguishing them from other defect types. Low coefficient of variation (CV percent) for EV and PF suggested that the data collection repeatability is acceptable, although a high CV percent was observed for TOF-c for some defect types in the deckboard sample.

Table 1. Energy value (EV), time of flight-centroid (TOF-c), and peak frequency of clear and defective wood of oak and poplar deckboards and stringers (Coefficient of Variation in parenthesis).

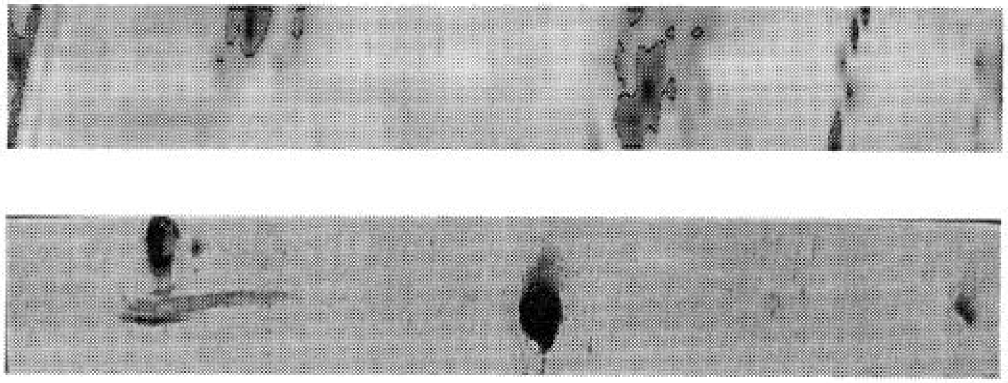
			Oak			**Poplar**	
Defects	**Sample**	**EV**	**TOF-c**	**PF**	**EV**	**TOF-c**	**PF**
Clear	*Deckboard*	-59.4 (1.5)	95.1 (2.7)	120.0 (1.0)	-60.0 (2.6)	99.4 (3.8)	119.6 (1.8)
	Stringer	-58.3 (1.9)	98.6 (3.1)	121.0 (1.1)	-64.1 (2.6)	106.6 (3.6)	119.9 (1.0)
Sound knot	*Deckboard*	-66.1 (12.5)	105.7 (13.8)	121.7 (1.5)	-66.2 (7.2)	95.7 (6.0)	120.8 (1.3)
	Stringer	-70.3 (6.7)	100.3 (3.8)	121.0 (2.3)	-79.4 (4.0)	107.7 (5.1)	119 (19.0)
Unsound	*Deckboard*	-83.4 (12.8)	143.4 (16.4)	122.2 (2.7)	-71.9 (10.3)	104.3 (10.8)	119.4 (2.1)
knot	*Stringer*	-75.8 (6.9)	100.7 (5.6)	123.6 (3.2)	-87.1 (10.7)	106.3 (6.7)	125.9 (7.5)
Decay	*Deckboard*	-80.8 (5.7)	123.8 (13.1)	120.0 (3.2)	-83.0 (6.5)	136.0 (15.4)	119.0 (2.3)
	Stringer	-98.9 (1.7)	125.3 (3.1)	223.4 (9.4)	-83.4 (10.1)	111.5 (5.7)	132.7 (14.6)
Bark pocket	Deckboard	-82.7 (9.8)	132.9 (15.7)	122.6 (4.4)	-78.9 (13.5)	127.9 (14.3)	126.5 (4.6)
	Stringer	-75.4 (9.2)	102.7 (9.7)	129.1 (11.4)	-81.1 (9.4)	113.9 (4.8)	125.9 (11.0)
Hole	*Deckboard*	-69.0 (3.2)	98.1 (3.7)	120.7 (0.6)	-93.9 (8.1)	201.1 (24.1)	123.0 (4.8)
	Stringer	-93.0 (1.4)	121.1 (5.1)	217.0 (9.8)	-95.3 (2.4)	116.7 (4.9)	212.1 (7.8)

Two-dimensional images were constructed using EV data from the multi-line scanning for deckboards, stringers, and cants. The examples of the reconstructed images for oak cants are shown in Figure 1. The reconstructed images are able to show the exact location and surface area of the defects. However, the reconstructed images are unable to identify defect type. The defects in the reconstructed images may a have greater surface area than the actual defect, particularly the position of defect on both faces deviated from perpendicular position, thus affecting ultrasonic signals. Also, grain deviation around the knot contributes a lot to the defect characterization, which can be hard to ascertain visually on the board.

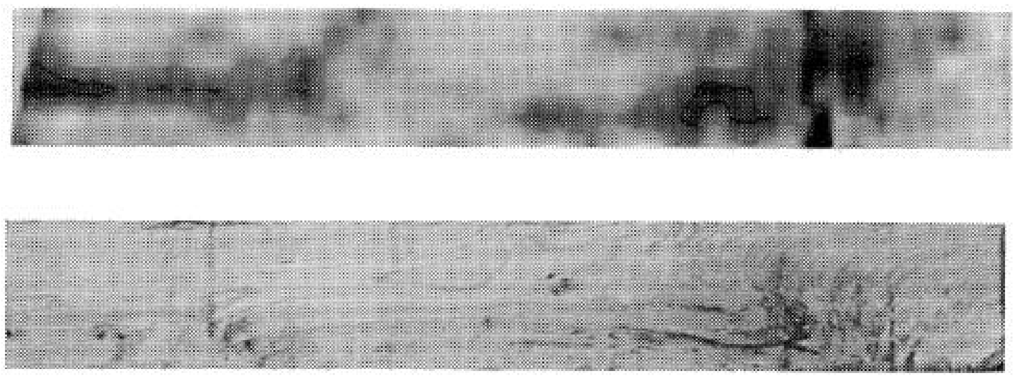
Defects were classified using multi-layer perceptron network (MLP), probabilistic neural network (PNN), and K-nearest neighbor (KNN). Each time, the network was trained with eight ultrasonic parameter values for a set of data and the testing was done with the other set of data. The most popular way of presenting the classification results is the "confusion table", which is simply a correlation matrix. Six-class classification results for poplar deckboards are shown in Table 2. Diagonal elements in the confusion matrix indicate correct classification results, while the other elements in the table are misclassifications. Similar results for oak stringers are shown in Table 3. The recognition rate was calculated as a percentage of the correct classification to the total number of data for each defect type. All three networks were able to classify defective wood efficiently and the recognition rate was over 95 percent.

Figure 1. Reconstructed images from the scanning data of EV and side view photos of the board- oak stringer (a), oak cant (b and c).

(a)



(b)



(c)

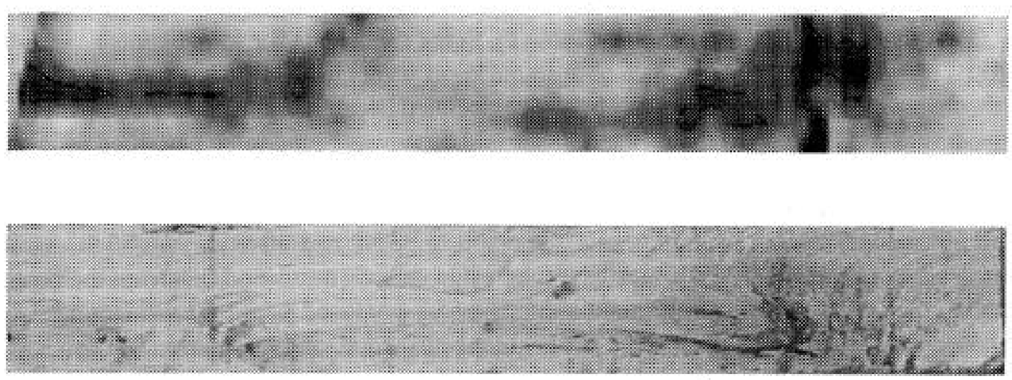


Table 2. The confusion table displays the number of correct and misclassified elements for MLP, PNN, and KNN classifiers using poplar deckboard data. Correct classification appears on the diagonal.

Defects		Clear Knot	Sound Knot	Unsound	Decay	Bark Pocket	Wane	Total	Corr. Classif. (%)
Clear	MLP	**138**	4	2	1	0	0	145	95.2
	PNN	**138**	5	1	1	0	0	145	95.2
	KNN	**145**	0	0	0	0	0	145	95.2
Sound Knot	MLP	**1**	**16**	3	0	1	0	21	76.2
	PNN	**1**	**15**	5	0	0	0	21	71.4
	KNN	**2**	**15**	4	0	0	0	21	71.4
Unsound Knot	MLP	0	2	**20**	1	4	2	29	70.0
	PNN	1	3	**19**	2	2	2	29	65.5
	KNN	0	5	**20**	4	0	0	29	70.0
Decay	MLP	0	2	1	**40**	1	6	50	80.0
	PNN	3	1	2	**34**	4	6	50	68.0
	KNN	0	1	4	**41**	0	4	50	82.0
Bark Pocket	MLP	0	0	1	1	**9**	2	13	69.2
	PNN	0	0	2	2	**8**	1	13	61.5
	KNN	0	0	1	2	**7**	4	13	53.8
Wane	MLP	0	0	1	5	7	**33**	46	71.7
	PNN	0	0	2	4	8	**32**	46	69.6
	KNN	0	0	2	4	6	**34**	46	73.9

The overall recognition: MLP = 84.2, PNN = 80.9, and KNN = 86.2

Sound and unsound knots can be classified properly using all of these networks, although the recognition rate in sound knots is little higher than unsound knot (Table 2). Some of the data for sound knots are misclassified as clear wood and unsound knots, whereas data of unsound knots were misclassified as sound knots and decay. This seems reasonable since unsound knots might have associated decay or splits, or are completely integrated with surrounding wood, leading to the misclassification. Decay was found to be classified efficiently with a high recognition rate using MLP, PNN, and KNN both for deckboards and stringers (Tables 2 and 3). The misclassification of decay mostly lies with holes and wane, since decay may have some void or fiber separation. Bark pockets showed lower recognition rates compare to decay and were misclassified as sound and unsound knots. Bark pockets, which are basically the inclusion of bark into wood, interrupt the continuity of the grain and may behave as sound and unsound knots. Wane is confused fairly equally among decay, bark pockets, and holes. This is expected since wane is the absence of wood, and the transducers can lose contact and generate very low energy signals, similar in value to decay, holes, and bark pockets.

The overall recognition rate, which is a percentage of the total correctly classified data to the total number of data, presented at the bottom of Tables 2 & 3 for each classifier. The classifier MLP and KNN have higher overall recognition rates than PNN for deckboards and stringers. The MLP was found to be the most suitable for classifying these defects. Similar results were also reported for MLP and KNN by Tiitta et al. (2001), although classifying several defect types in a single board is more complicated than classifying the degree of severity in a single defect. Usually, MLP provides very good results if it is correctly used or when the level of learning or network size is suitable. Whereas, the KNN classifier is non parametric and obviously the easiest to use and works quite well with linear or nonlinear data.

Table 3. The confusion table displays the number of correct and misclassified elements for MLP, PNN, and KNN classifiers using oak stringer data. Correct classification appears on the diagonal.

Defects		Clear Knot	Sound Knot	Unsound	Decay	Bark Pocket	Wane	Hole	Total	Corr. Classif.(%)
Clear	MLP	**69**	1	0	1	1	0	0	72	95.8
	PNN	**70**	2	0	0	0	0	0	72	97.2
	KNN	**72**	0	0	0	0	0	0	72	100.0
Sound Knot	MLP	3	**22**	2	0	2	0	0	29	75.9
	PNN	2	**20**	2	0	5	0	0	29	70.0
	KNN	2	**21**	3	0	4	0	0	29	72.4
Unsound Knot	MLP	0	6	**14**	0	4	0	0	24	58.3
	PNN	2	5	**12**	0	5	0	0	24	50.0
	KNN	0	5	**16**	0	3	0	0	24	66.7
Decay	MLP	0	1	0	**55**	1	1	4	62	88.7
	PNN	0	0	0	**49**	1	0	12	62	79.0
	KNN	0	0	0	**51**	1	1	9	62	82.3
Bark Pocket	MLP	2	3	5	2	**24**	1	0	37	64.9
	PNN	1	6	6	1	**22**	0	1	37	59.5
	KNN	1	6	8	0	**21**	0	1	37	56.8
Wane	MLP	0	0	0	2	2	**11**	7	20	55.0
	PNN	0	0	0	3	2	**12**	3	20	60.0
	KNN	0	0	1	2	2	**11**	4	20	55.0
Hole	MLP	0	0	0	4	1	10	**30**	45	66.7
	PNN	0	0	0	2	0	12	**31**	45	68.9
	KNN	0	0	0	6	0	14	**25**	45	55.6

The overall recognition : MLP=77.9, PNN=74.8, and KNN=75.1

CONCLUSIONS

Energy related parameter was found to be more sensitive to sound and unsound knots, decay, bark pockets, and hole for oak and yellow-poplar deckboards and stringers. Because all defect types present a transmission medium that is different from clear wood, there is a large loss of energy at the interface. Unsound knots, decay, and bark pockets have shown similar energy loss for deckboards. The TOF measurements, however, were not found to be very effective at discriminating defects. PF can be used as an effective tool for discriminating decay and holes.

The multi-layer perceptron (MLP), probabilistic neural network (PNN), and k-nearest neighbor (KNN) were found to be suitable for classifying sound and unsound knots, decay, bark pockets, wane, and holes for both deckboards and stringers. All these classifier networks are able to distinguish defective wood from clear wood with high recognition rate. A few sound knots were misclassified as clear wood or unsound knots. Decay can be classified more accurately than the other defects and bark pockets were misclassified as decay and holes. Wane and holes have similar ultrasonic characteristics and misclassification usually occurred with decay and bark pockets. The MLP showed the highest overall recognition rate for classifying these defects. Two-dimensional reconstructed images were able to provide the exact location and surface area of the defects.

This study suggested that sorting and grading of pallet parts are possible using on-line ultrasonic scanning. The unsound defect volume in cants can be determined using reconstructed images, and thus, optimized sawing practices can increase the value of material obtained from cants.

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