CLASSIFYING DEFECTS IN PALLET STRINGERS BY ULTRASONIC SCANNING

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ABSTRACT

Detecting and classifying defects are required to grade and sort pallet parts. Use of quality parts can extend the life cycle of pallets and can reduce long-term cost. An investigation has been carried out to detect and classify defects in yellow-poplar (*Liriodendron tulipifera,* L.) and red oak (*Quercus rubra,* L.) stringers using ultrasonic scanning. Data were collected for sound and unsound knots, bark pockets, decay, holes, and wane using rolling transducers in a pitch-catch arrangement. Data from eight ultrasonic variables—energy, pulse length, time of flight (TOF)-amplitude, TOF-energy, TOF-centroid, energy value, energy pulse value, and peak frequency—were used to classify defects. Three different types of classifiers were used to categorize defects—a multi-layer perceptron network (MLP), a probabilistic neural network (PNN), and a k-nearest neighbor (KNN) classifier. Mean values for the energy variables demonstrated statistically significant differences between clear wood and defects and among defect types. Mean values for the TOF variables did not differ significantly between clear wood

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and knots. All three types of classifiers were able to distinguish defected from clear wood in oak with accuracies above 95%; accuracies for yellow-poplar were somewhat lower for the MLP and PNN classifiers. Among the defect classes, decay exhibited the highest recognition rate for both yellow-poplar and oak. Wane and holes in oak were readily confused owing to their common loss of transducer contact. Overall accuracy at the data-point level varied from 69–78%. Simple post-processing operations are expected to improve that substantially. Based on accuracy performance alone, the MLP and KNN appear equally preferable for this task.

Keywords: Ultrasonic scanning, nondestructive testing, transducer, defect classification, neural network.

INTRODUCTION

Typically, wooden pallets consist of two parts—stringers, the structural central members that carry the load, and deckboards, the top and bottom parts that provide dimensional stability and products placement. Pallets are manufactured in many ways depending on size, pallet use, and also number and positions of stringers and deckboards. Usually, pallet parts are produced from solid wood (lumber) or from the center portion (cant) of logs. These cants have a high percentage of defects and have less market value for other solid wood products, which makes them attractive as a raw material source for pallets.

The most common defects found in pallet parts are sound knots, unsound knots, cross grain, bark pockets, decay, holes, splits, shake, and wane. The extent and severity of these defects often depend on the wood species. A recent study (Araman et al. 2003) on cants showed that different species vary in the volume of defects found in a typical cant. Defect volume can comprise above 30% of the total volume of a cant. Because the location and extent of pallet part defects contribute to the strength and durability of a pallet, high-grade pallets (containing fewer defects) have a longer life cycle and promote multiple trips per pallet. Therefore, high-quality pallet parts are desired. Manual grading and sorting is a slow and inaccurate process, so an automated inspection system could be very useful to detect defects and sort pallet parts. A study by Schmoldt et al. (1993) demonstrated the profit potential for such an automated inspection system.

In the past few years, many researchers have examined ultrasonic inspection of wood for defects, primarily in surfaced lumber (McDonald 1980; Ross et al. 1992; Bradshaw et al. 2000; Fuller et al. 1995; Niemz et al. 1999; Raczkowski et al. 1999; Karsulovic et al. 2000; Halabe et al. 1996). Most of these ultrasonic investigations have used transmission time to characterize defects. Measurement of transmission time may be useful when there is only a single defect type in a board or where transmission velocity is diagnostic for the defect types of interest. Certain defect types, however, do not respond well to transmission time measurements, but respond, instead, to other ultrasonic variables, e.g., peak amplitude, energy, centroid time, frequency domain energy, etc. Studies by Halabe et al. (1993, 1994, 1996) showed that frequency domain analysis is very useful for detecting decay. Bradshaw et al. (2000) reported that insertion loss and energy measurements provide valuable information for detecting wetwood in red oak lumber. Still, before an automated pallet part inspection system can be operational, it must be able to reliably locate, distinguish, and measure a variety of different defect types. This capability has not been demonstrated to date.

An ongoing research project aims to develop an automated pallet part inspection system (Schmoldt et al. 1994, 1997; Kabir et al. 2000, 2002). However the classification step in defect detection is a difficult and complicated task using any online inspection system. Differences exhibited by ultrasonic variables across several defect types can be small, making classification difficult. The degree of severity for any single defect is somewhat easier, however, as reported by Tiitta et al. (2001).

This paper presents some initial classification results for defects in two species of wooden pallet stringers using ultrasonic measurement variables as feature vectors. Three different types of classifiers are used in this experiment. Their ability to distinguish between various defect types and clear wood are reported.

MATERIALS AND METHODS

Scanning and data collection

Fresh, unplaned yellow-poplar (*Liriodendron tulipifera,* L.) and red oak (*Quercus rubra,* L.) stringers of varying lengths were collected from a local sawmill. They were kept in cold storage to reduce their drying rate, and the moisture content of the stringers was maintained approximating the fresh-cut state or above the fiber saturation point. Eighteen stringers were scanned for each species, three for each of six defect types. Each stringer also contained clear wood, which is the only non-defect classification. The average length, width, and thickness of the stringer were 122 cm, 10 cm, and 3.8 cm, respectively. Defects examined in this study are sound and unsound knots, bark pockets, holes, decay, and wane. Six scan lines were marked longitudinally along the face of each stringer 12.5 mm apart, and data were collected every 2.5 mm along each scan line. The scanning was conducted across the thickness of the board, which is perpendicular to the growth ring (either radial or tangential or both). From this data set, a classification data set was generated by randomly selecting samples from each class.

The scanning equipment used in these tests was manufactured by the Ultrasonic Group, Forest Products Division of Perceptron Inc. The system consists of in-feed and out-feed roll beds, two sets of pinch rollers for part movement, and two rolling transducers mounted in an ultrasonic ring. Details of the equipment and materials handling were described elsewhere (Kabir et al. 2002). Stringers 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. Data were collected, stored, and processed by LabView™ software modules. The scanning speed was 220 ft/min, and the desired spatial resolution (number of waveforms per centimeter; 4 in this study) can be achieved by controlling roller speed and the number of pulses per second. We chose higher scanning speed since scanning speed does not have significant effect on the data collection (Kabir et al. 2002). Each board was scanned three times to ensure consistency of the data collection, although the repeatability and reliability of the data collection are acceptable as mentioned in Kabir et al. (2002). All measurements were carried out at 120 kHz transmitting frequency, and received signals were sampled at 500 kHz.

Ultrasonic variables

Ultrasonic scanning involves recording signal voltage measurements 500,000 times per second. From these data, eight variables were calculated—three for time of flight, three for pulse energy, and one each for pulse duration and peak frequency. Specifically, variables included pulse length (PL), time of flight-centroid (TOF-c), time of flight-energy (TOF-e), time of flight-amplitude (TOF-a), energy, energy value (EV), energy/pulse value (EPV), and peak frequency (PF). These are described below.

The wave energy of the received signal can be expressed as the time integral of the voltage:

$$E = \int v^2(t)\, dt \qquad (1)$$

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:

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

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

Time of flight (TOF) measurements 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%, then TOF-energy is simply the time at which the integral value reaches 40% of the final value. Similarly, TOF-amplitude is the time at which the amplitude of the signal first reaches, for instance, 40% 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.

For each data point, a feature vector was constructed that consists of the eight ultrasonic variables mentioned above. Each feature vector was also paired with a class designation as determined by a visual inspection of the data point on the stringer. For yellow-poplar, hole defects were not present in the specimens collected, and so the total number of classes was reduced to six. A total of 289 feature vectors were created for oak and 268 for poplar, and were used with each of the classifiers described below.

Defect classification

Three different types of supervised classifiers were used to discriminate pallet part defects. These are a multilayer perceptron network (MLP), a probabilistic neural network (PNN), and a k-nearest neighbor (KNN) classifier. Theory and details of these classification methods can be found in Duda and Hart (1973), Specht (1990a), Gonzales and Woods (1992), and Tiitta et al. (2001). The classification methods were applied to the nine-element feature vectors described above (eight variables plus one class output value). For the MLP and PNN classifiers, we used tenfold cross-validation. In this approach, the entire data set is partitioned into 10 subsets, and an initial classifier is trained on all the data from nine partitions and tested on the tenth. The testing partition is then reinserted back into the full data set and another partition is removed for testing. Then, a second-stage classifier is trained on the revised nine partitions and tested on the new tenth partition. This replacement/training/testing cycle is repeated until all ten test partitions have been used. The final classification rate is the average of all ten classifiers.

Artificial neural networks are one of the most commonly used models for pattern classification. The multilayer perceptron (MLP) network, which consists of a large number of simple, interconnected, structurally identical processing elements (PEs), is the most frequently used type of network. Network weights are adjusted using back-propagation supervised training to gradually coerce the network output toward the known target. A nonlinear tangent sigmoid function was used as the transfer function that converts weighted inputs from each PE into an output signal. Our MLP network consists of an eight-node input layer (corresponding to the feature vector elements), two hidden layers with 16 and 10 PEs, respectively, and a 1-of-N output layer containing seven PEs (one for each defect and one for clear wood, a total of six for yellow-poplar). We reasoned that two hidden layers might offer more sophisticated mappings than a single hidden layer to help describe the decision boundaries between classes. We have obtained better results when the dimensionality of the hidden layer is more than twice the input's dimensionality, so we used 16 PEs for the first hidden layer. The second hidden layer has 10 PEs (greater than the number of PEs in the output layer). Then, back-propagation trains the network until the performance goal (mean square of the network error = 0.02) is met.

Probabilistic neural networks are a class of artificial neural network that combines some of the best attributes of statistical pattern recognition and feed-forward neural networks. Because PNNs have an ability to approximate the probability density function of the underlying distribution inherent in the example data set, they guarantee convergence to a Bayesian classifier, if enough training examples are provided. Therefore, PNNs are suitable for supervised classification problems (Specht 1990b). We used a two-layer network for the PNN. The first layer contains radial basis functions as the kernel and the second layer is a competitive network, where the PE receiving the greatest value for its input has an output of 1. All the other second-layer PEs have outputs of 0.

A *k*-nearest neighbor classifier is a nonparametric classifier. Leave-one-out training/testing is often used, so the training data for each output category represent a class, and the one unclassified pattern is classified by finding the nearest-neighbor class(es). Statistically, more reliable results can be achieved by using more than one nearest-neighbor class. The *k*-nearest neighbor classifier finds the *k*-nearest neighbors to the target data point based on some distance metric. The final class is chosen from those nearest neighbors by some voting mechanism. The leave-one-out method repeats this process for every sample. In our implementation of the KNN classifier, a value of $k = \sqrt{N}$ and Euclidean distance were used, where N represents the number of sample data points. A simple plurality count was used as the voting mechanism.

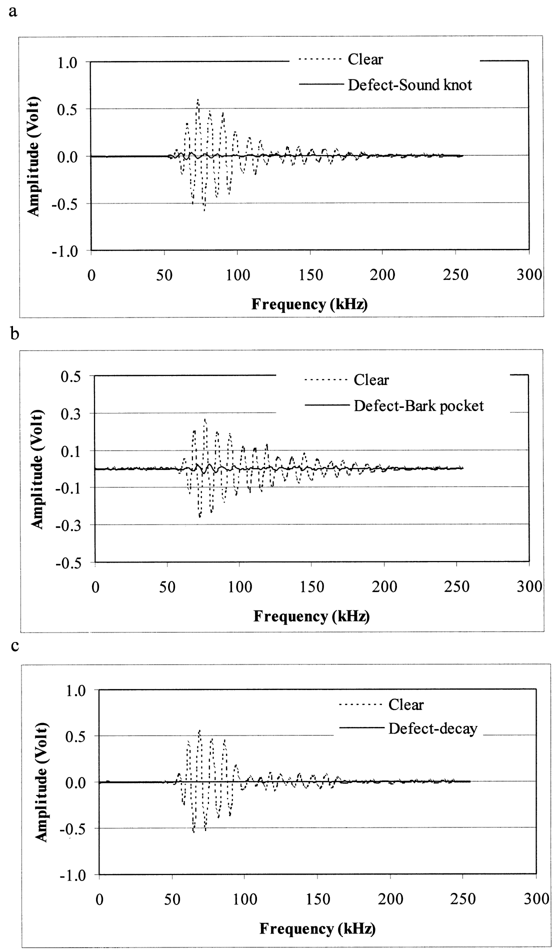

FIG. 1. Signal amplitude in the frequency domain for ultrasonic signals through clear and defected wood, (a) sound knot in oak, (b) bark pocket in yellow-poplar, and (c) decay in oak.

RESULTS AND DISCUSSION

Amplitude waves for ultrasound signals propagating through clear and defected wood are shown in Fig. 1. Signals for defected wood (sound knots, bark pockets, and decay) in both yellow-poplar and oak are attenuated to the point that signal strength barely diverges from 0v. Because defects in wood produce defect-clear wood interfaces, ultrasonic signal energy is lost as the elastic wave's transition from one medium to another. So, energy loss alone is a reliable indicator of defect presence. Other signal characteristics, however, are needed to

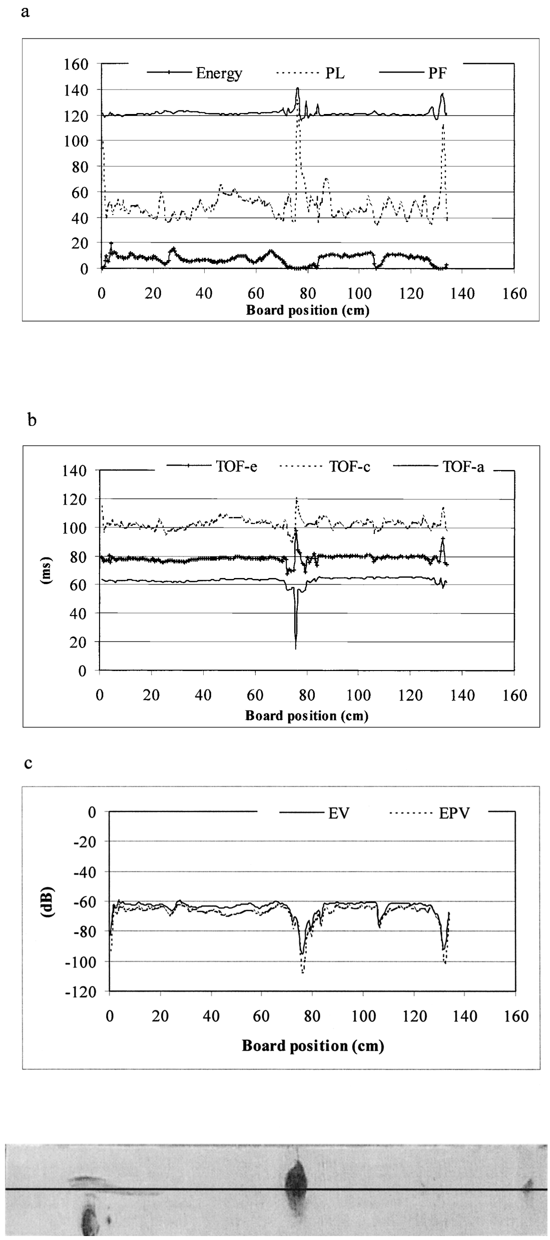

FIG. 2. The response of different ultrasonic variables to the unsound knot of yellow-poplar stringer, a) energy, PL, and PF, b) TOF-e, TOF-c, and TOF-a, and c) EV and EPV.

distinguish between defect types. Figure 2 depicts the effect of unsound knot on the ultrasonic variables of yellow-poplar stringer. All variables were affected significantly by unsound knot. The response of different defect types to the ultrasonic variables was discussed elsewhere (Kabir et al. 2002).

Tukey's *t*-test results for different defect types and ultrasonic variables in oak and yellow-poplar are presented in Table 1. In each case, mean values of the ultrasonic variables for each defect type were tested. Mean values for clear wood energy measurements are significantly different from defected wood both for oak and yellow-poplar, but there exist almost no differences in mean values between defect types. While EV and EPV also have clearly different mean values for clear wood and defects, they also show differences between mean values for many defect types. This makes EV and EPV good candidates for classifying defects. The variables PL, TOF-a, TOF-e, TOF-c also showed significance differences between mean values for clear and defected wood. However, there are no significant differences between mean values for clear wood and mean values for either sound or unsound knots. Because both hole and wane defects result in the transducers losing good contact with the wood, their mean values are difficult to distinguish for all ultrasound variables.

Feature vectors calculated from scan data for each species were classified using a multilayer perceptron network, a probabilistic neural network, and a *k*-nearest neighbor classifier. An effective way to present classification results is a ''confusion matrix,'' where each row displays how the row's category (the true class), e.g., sound knot, was classified. Seven-label classification results for oak stringers are shown in Table 2; corresponding results for yellow-poplar appear in Table 3. Diagonal elements in the confusion matrix indicate correct classification results, while the other elements in the table are misclassifications. Classification accuracies for each defect type and each classifier type appear in the last column in each table, while overall classification accuracies appear in the bottom-right corner of each matrix.

Overall classification accuracy of the MLP

TABLE 1. *Tukey's t-test results indicate, for each ultrasonic measurement variable, where mean values for different defect types differ significantly in oak and yellow-poplar stringers. Defect types are significantly different at $\alpha = 0.01$ unless noted otherwise*.*

Species	Ultrasound variables[a]							
	Energy	PL	TOF-a	TOF-e	TOF-c	EV	EPV	PF
Oak	C-all	C-U,B,W,H K-D,W,H U-D,W,H D-C,B,W* B-W,H	C-D,B,W,H K-D,W,H U-D,W,H D-B B-W,H	C-D,W,H K-D,W,H U-D,W,H B-	C-D,B,W,H K-D,W,H U-D,W,H D-B B-W,H W-H*	C-all K-all U-D,W,H D-all B-W,H	C-all K-all U-D,W,H D-all B-W,H	C-D,W,H K-D,W,H U-D,W,H D-B,W* B-W,H
Yellow-Poplar	C-all K-all	C-all K-W U-W D-W*	C-W K-W*	C-D,W K-D,W U-D,W D-W* B-W	C-D,B,W K-D*,B,W U-D,B,W D-W	C-all K-all U-B,W D-W B-W	C-all K-all W-U,D,B	C-D*,W W-K,U,D,B

[a] C Clear wood, K sound knot, U unsound knot, D decay, B bark pocket, W wane, and H hole.
* Significant at $\alpha = .05$.

TABLE 2. *The confusion matrix displays the number (and types) of misclassifications (off-diagonal elements) for MLP, PNN, KNN classifiers applied to oak stringers. Correct classifications appear on the diagonal.*

True class		Clear	Sound knot	Unsound knot	Decay	Bark pocket	Wane	Hole	Total	Accuracy (%)
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	30	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	22	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
Total	MLP	74	33	21	64	35	23	41	**291**	77.9
	PNN	75	33	20	55	35	24	47	**289**	74.8
	KNN	75	32	28	59	31	26	39	**290**	75.1

TABLE 3. *The confusion matrix displays the numbers (and types) of misclassifications (off-diagonal elements) for MLP, PNN, KNN classifiers applied to yellow-poplar stringers. Correct classifications appear on the diagonal.*

True class		Clear	Sound knot	Unsound knot	Decay	Bark pocket	Wane	Total	Accuracy (%)
Clear	MLP	**62**	7	0	0	0	0	69	89.9
	PNN	**56**	12	0	1	0	0	69	81.2
	KNN	**68**	1	0	0	0	0	69	98.5
Sound knot	MLP	6	**43**	3	0	4	0	56	76.8
	PNN	7	**42**	3	0	4	0	56	75.0
	KNN	9	**40**	5	0	2	0	56	71.4
Unsound knot	MLP	0	5	**21**	2	0	3	31	67.7
	PNN	0	6	**20**	3	0	2	31	64.5
	KNN	0	5	**19**	2	1	4	31	61.3
Decay	MLP	0	2	0	**32**	1	3	38	84.2
	PNN	0	1	2	**29**	3	3	38	76.3
	KNN	0	3	1	**30**	2	2	38	78.9
Bark pocket	MLP	0	0	2	3	**13**	0	18	72.2
	PNN	0	0	0	4	**9**	5	18	50.0
	KNN	0	2	0	3	**11**	3	19	61.1
Wane	MLP	0	1	5	13	0	**37**	56	66.1
	PNN	1	2	8	9	6	**30**	56	53.6
	KNN	0	0	3	11	0	**42**	56	75
Total	MLP	68	58	31	50	18	43	**268**	77.6
	PNN	64	63	33	46	22	40	**268**	69.4
	KNN	77	51	28	46	16	51	**269**	78.4

for red oak is slightly higher (although not statistically significant) than either the PNN or the KNN. For yellow-poplar, accuracies for the MLP and KNN classifiers are statistically indistinguishable, whereas the MLP is significantly better than the PNN classifier (α = .026). Similar classifier results (with a single defect type, decay) were also reported for MLP and KNN classifiers by Tiitta et al. (2001). Typically, MLP classifiers provide very good results if network parameters are chosen carefully. On the other hand, KNN classifiers are non-parametric, extensive training is not required (beyond setting *k*, the distance metric, and the voting method), they are easy to use, and they work quite well with either linear or nonlinear data.

By examining row and column totals, we can make a few observations about classification using these data. For oak stringers, there seems to be a general "over-classification" of clear wood, sound knots, and wane, i.e., more samples are assigned to those classes than actually appear in the data set. Unsound knot, decay, bark pocket, and hole categories are generally "under-classified," although not uniformly so by all oak classifiers in all cases. For yellow-poplar stringers, decay defects are strongly over-classified and wane defects are strongly under-classified. All three types of classifiers are able to distinguish clear wood from defected wood in oak with greater than 95% accuracy. Clear wood classification accuracies for yellow-poplar are not nearly as uniformly high. For both species, classification accuracies for decay and sound knots were the next highest. For the remaining classes, classification accuracies are much lower and vary between classifier types. While under- and over-classifications point to potential performance problems, we need to examine those misclassifications in more detail to understand how they affect strength-reducing defects.

In the case of oak, only sound knots and bark pockets exhibited some misclassifications as clear wood, and then only a few. When bark pockets are large (and consequently highly strength-reducing), this misclassification is less likely to occur (ultrasound signals should be noticeably different otherwise). Unsound knots are primarily confused as sound knots or bark pockets. This is not unexpected, because (1) many unsound knots can have included bark, and (2) parts of unsound knots can also be sound. Most decay misclassifications occur as holes—both are serious strength-reducing defects, so confusion between them is not too serious. Bark pocket defects exhibit misclassifications with every other category, due to their co-occurrence with many other defect types. Wane is confused fairly equally among decay, bark pockets, and holes. This is expected because wane is the absence of wood, and so the transducers can lose contact and generate very low energy signals, similar in value to decay, holes, and bark pockets. Between ¼ and ⅓ of hole defects were misclassified as wane, which again is due to poor transducer contact. Most of these misclassifications in oak, then, are reasonable given what we know about defect manifestations and ultrasound signal generation and propagation.

There are significantly more misclassifications of clear wood for yellow-poplar than for oak stringers. The KNN classifier performed significantly better than the MLP and PNN for clear wood, which contributed to its overall high accuracy. The MLP, on the other hand, performed moderately well across all defects. The PNN exhibited generally good accuracy for many defects, but it faired quite poorly on wane and bark pocket defects, creating low overall accuracy. The pattern of misclassifications for sound knots was similar to oak. However, unsound knots were confused with wane and decay, rather than bark pockets (as in oak). Without any hole defect type included in the yellow-poplar data, decay, bark pockets, and wane were confused with all other defects (not clear wood). Because hole defects have similar ultrasound signals to each of those three defects, their absence may have decreased the ability of the classifiers to discriminate the remaining classes in parameter space.

CONCLUSIONS

Based on statistical tests of mean values, energy variables, particularly EV and EPV, appear to have good discriminating power to distinguish between clear wood and defects in these two species of stringers (Table 1) seemingly contradicting the findings of other studies, e.g., McDonald (1980) and Schmoldt et al. (1997). Our explanation for this discrepancy is twofold: (1) we are using thicker specimens—previous studies used nominal 1-inch lumber or thinner (pallet deckboards), and (2) our TOF variables are conditioned on aspects of the *entire* waveform, rather than just arrival time of the leading edge (the typical TOF measurement). With thicker specimens, much of the sound-knot cross-section, through which ultrasound signals propagate, can contain considerable clear wood volume. In this case, TOF values may not be appreciably different between clear wood regions and sound-knot regions. For thinner materials, the ratio of clear wood volume to true knot volume around a knot defect is much lower, resulting in more homogenous knot regions and more distinguishable differences in TOF values. Furthermore, because the TOF variables used here are conditioned on the entire waveform, these TOF variables can behave quite differently and may have little relation to ‘‘leading edge’’ TOF measurements.

Differences in classifier performance between species are somewhat surprising. If the PNN classifier had performed better for yellow-poplar wane and bark pocket defects, the overall results would have been quite similar for both species. In that case, neither classifier would have demonstrated a clear performance advantage. Given the current feature vectors, though, it appears that either the MLP or the KNN is the preferred type. In particular, one might select the KNN based on its simplicity of use and its high accuracy for distinguishing clear wood from defects in both species.

The current data and analyses are relatively preliminary. While overall accuracy values are not as high as is desirable, they reflect only individual measurements and analyses at 2.5-

mm spatial resolution. As part of an eventual scanning process, we will be generating a 2-dimensional image of each stringer. Initial classifications of each data point would then be refined in a post-processing step, wherein multiple data points (pixels) would be used to label any region as belonging to a particular class. At that point, then, spatial information could be used to improve classification. This could include both shape and location, e.g., many of the wane, decay, and hole misclassifications could be eliminated by fairly simple spatial analysis. Probably one-half of the current errors could be removed immediately. Many others could be eliminated by simple morphological operations that reclassify individual data points based on immediately surrounding data points. At the same time, we will need to examine entire-defect labeling accuracy, rather than the individual, data-point labeling accuracy reported here. Based on the current results, though, we expect that all but the smallest defects will be readily distinguishable.

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