Characterization of Defects in Lumber Using Color, Shape, and Density Information

B. H. Bond
Department of Forestry, Wildlife, and Fisheries
University of Tennessee
Knoxville, TN, USA

D. E. Kline
Department of Wood Science and Forest Products
Virginia Polytechnic Institute and State University
Blacksburg, VA, USA

P. A. Araman
USDA Forest Service
Southeastern Experiment Station
Blacksburg, VA, USA

Abstract - *To help guide the development of multi-sensor machine vision systems for defect detection in lumber, a fundamental understanding of wood defects is needed. The purpose of this research was to advance the basic understanding of defects in lumber by describing them in terms of parameters that can be derived from color and x-ray scanning technologies and to demonstrate how these parameters can be used to differentiate defects in lumber. Color and x-ray images of intergrown knots, bark pockets, stain/ mineral streak, and clearwood were collected for red oak (Quercus rubra), Eastern white pine, (Pinus strobus), and sugar maple, (Acer saccharum) Parameters were measured for each defect class from the images and class differences were tested using analysis of variance techniques (ANOVA) and Tukey's pair-wise comparisons with = 0.05. Discriminant classifiers were then developed to demonstrate that an in-depth knowledge of how defect parameters relate between defect types could be used to develop the best possible classification methods. Classifiers developed using the knowledge of defect parameter relationships were found to provide higher classification accuracies for all defects and species than those which used all parameters and where variable selection procedures had been used.*

Keywords: *multi-sensor, defect detection, lumber, discriminant analysis.*

1. Introduction

Facing price increases, reduced quality, and shortages in raw material, the wood products industry must aggressively explore innovative processing technologies if they are to survive in an increasingly complex and competitive environment. A critical need for improved processing in the wood products manufacturing industry is the development of a system that can efficiently and cost-effectively convert existing wood raw materials into high-quality products. The development of new processing technologies will require a sensing system that can automatically inspect wood and accurately pinpoint defects. Such a scanning system would provide accurate and consistent identification of the type and location of defects for either removal or grading purposes. Such a system could also reduce labor costs, improve yield, and allow for more intelligent utilization of solid wood resources.

An automatic defect detection system would require some type of scanning technology. Many different sensing methods have been applied to inspection of wood including optical, ultrasonic, microwave, nuclear magnetic resonance, and x-ray sensing [1,2]. While research on each of these sensing methods has produced marked results in recent years, commercial applications based on these methods have not been able to meet the industry's expectations. Accurate and reliable defect detection has been a challenge mainly due to the lack of knowledge about the enormous variability in the nature and condition of the wood materials processed by the industry, and by limitations of the individual sensing technologies.

While different types of sensors for automatic defect detection in wood have been studied, little work has been done to investigate the combination of different sensors in one system [3,4,5]. It has been proposed that a multi-sensor scanning system will be required to drive new automation technologies [6]. With the integration of multiple sensor information, the accuracy of an automatic defect inspection system can be substantially improved.

To help guide the development of multi-sensory machine vision systems for detecting defects in lumber a fundamental understanding of the nature of defects is needed. By understanding how defects are represented by various sensors, better detection algorithms can be generated. The purpose of this research was to advance the basic understanding of defects in lumber by describing them in terms of parameters that can be derived from color and x-ray scanning technologies and to demonstrate how these parameters can be used to differentiate defect classes.

2. Experimental Methods

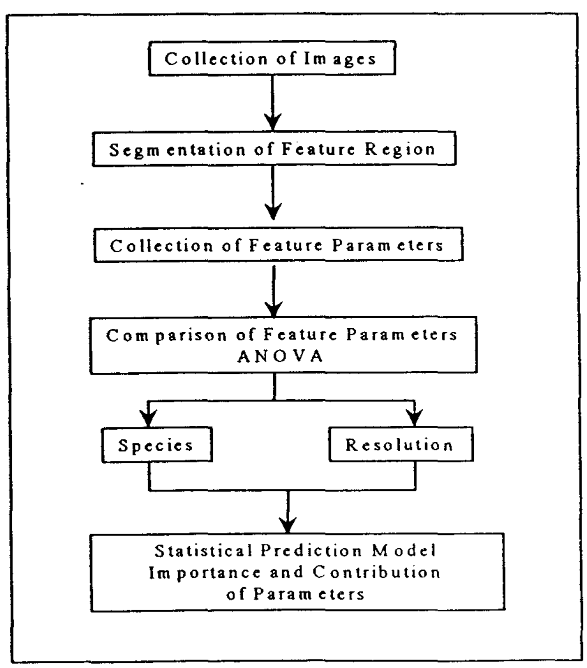
Color and x-ray images of intergrown knots, bark pockets, stain and mineral streak, and clearwood were collected for red oak, *(Quercus rubra)*, Eastern white pine, *(Pinus strobus)*, and sugar maple, *(Acer saccharum)* using equipment designed at Virginia Tech for multi-sensor scanning of lumber [7]. The system employs a color line scan camera and a linear array x-ray detector. A description of the scanning setup is presented in Bond [8]. The resolution of color and x-ray images was 30 pixels per inch across the width of the board and 16 pixels per inch along the length of the board. Fifteen to twenty samples of each defect type were selected and scanned. The defects scanned were identified in lumber that was obtained from several furniture manufactures in the state. Specimens were scanned at an 8% moisture content. The defects studied were manually segmented from clearwood regions using image analysis software. The measures and notations listed in Table 1 were then quantitatively measured for each defect type.

Comparisons were made for each measured parameter between defect types using analysis of variance techniques (ANOVA) and Tukey's pairwise comparisons with $\alpha = 0.05$. The purpose of these comparisons was to determine if the measured parameters had significant differences between defects. The relationships of parameters to defect classes were used to select variables for defect classification. Discriminant classifiers were then developed and compared to demonstrate that an in-depth knowledge of how parameters relate between defect classes could be used to develop the best possible classification method. An outline of the methods is presented in Figure 1.

Table 1. Measurements collected for each defect and their notation.

Notation	Parameter Measured From each defect	Image Used to Measure
R_m	Red mean	Color
G_m	Green mean	
B_m	Blue mean	
R_s	Red standard deviation	
G_s	Green standard deviation	
B_s	Blue standard deviation	
H_m	Hue mean	
S_m	Saturation mean	
I_m	Intensity mean	
H_s	Hue standard deviation	
S_s	Saturation standard deviation	
I_s	Intensity standard deviation	
ASP	Aspect	Color
RND	Roundness	
X_m	Density mean	X-ray
X_s	Ddensity standard deviation	

Figure 1. Outline of experimental methods.



3. Statistical Comparison of Defect Classes

3.1 Single Species

The number of significant differences between defect classes for each parameter and species are listed in Table 2. The results of statistical analysis indicate that red oak will require more classification variables due to the small number of significant differences between defect classes for most of the parameters as shown in Table 2. Further analysis indicates that the magnitude of mean differences between defect classes was smallest for red oak, suggesting that red oak defect types will be more difficult to classify.
It was predicted that for all species the R_m, G_m, and B_m parameters would provide good differentiation between all defect types. Based on the number of significant differences between defect classes the H_m and I_m parameters should be included in the classification model for hard maple and the S_m and I_m parameters should be used for white pine. All species should include the I_m as a classification variable. The color standard deviation parameters were found to be species dependent.

Table 2. Number of significant differences between defect type for each parameter and species.

Number of Significant Differences Between Defect Classes	Species		
	Red Oak	Hard Maple	White Pine
0	S_m		
1		B_s	B_s
2	X_m,G_s,		
3	H_m, R_s,B_s,H_s,I_s	ASP, RND, G_s, H_s, I_s	H_m, H_s
4	ASP, S_s,X_s	S_m, R_s, X_s	X_m, G_s
5	R_m, G_m,B_m, I_m,RND	H_m, X_m, S_s	S_m, ASP, RND, R_s, S_s, I_s, X_s
6		R_m, G_m,B_m, I_m	R_m, G_m,B_m, I_m

The X_m and X_s parameters should benefit all species defect classification methods, but will provide more benefit in the white pine and hard maple classifiers. The density difference between knots and clearwood was found to be greater in pine than in hardwoods, indicating that density will provide a better separation variable for pine than hardwoods.

Shape measures should be included in defect classifiers. However, both shape measures provide similar information between defect classes; therefore, only one will be required.

Based on the number of significant differences between defects it is suggested that for all species both color mean and standard deviation parameters will provide good differentiation between defect classes. The parameters suggested for classification are listed in Table 3.

Table 3. Suggested parameters for defect differentation.

Species	Suggested Parameters for Defect Differentiation
Red Oak	R_m,G_m, B_m, H_m, I_m, X_m, ASP,I_s, X_s
Hard Maple	R_m, G_m,B_m, H_m, S_m,I_m, X_m, ASP, I_s, X_s
White Pine	R_m, G_m, B_m, S_m,I_m, X_m, ASP, RND, X_s R_s

3.2 Multi-Species

Differences between parameters were shown to exist between species for all defects except bark pockets. Bark pockets were the only defect with equal color parameters for all species.

While many defect types had significantly different parameters between species, hard maple and white pine were shown to have several similar color parameters, indicating that species with greater I_m parameter values were more closely related. Color parameters of defect classes were normalized based on clearwood parameter values and compared using ANOVA It was discovered that the I_m parameter of a defect for a particular species was found to related to the clearwood I_m parameter. This relationship could be used to develop a multi-species classifier where defect values are normalized based on the clearwood I_m parameter for each species.

3.3 Resolution

To determine the affect of resolution on the relationships of the parameters, two different spatial resolutions were compared for each defect class and for all measured parameters. The two resolutions compared were 30 x 16 pixels per inch resolution and a 15 x 8 pixels per inch. The regional parameters of each defect class were then measured and compared using analysis of variance techniques. No significant differences ($\alpha = 0.05$) were found between the resolutions of regional parameters in any of the defects or species; therefore, it is concluded that halving the resolution for these defects in lumber will not affect the parameter relationships. It must be noted that the defect regions measured were segmented manually to ensure that all measures were related to the actual defect. This measurement technique is a limitation for comparison of resolution. If other segmentation methods were used, then the boarders of regions would possibly include non-defect material and thus change the results. Because resolution was not found to affect parameter relationships, this variable will not be discussed in the modeling of defect parameters.

Once the statistical differences between defect classes had been determined for all the measured parameters, this information was used to develop classification functions. The classification functions were used to demonstrate that the parameters chosen were indeed the best for classification, to determine the contribution of each parameter in differentiating defect classes, to model the defects using parameters, and compare color spaces.

4. Defect Classification Using Color, Shape, and Density Parameters

4.1 Single Species

Discriminant classifiers were developed using forward, backward variable selection methods, randomly selected variables, and all possible variable combinations. Discriminant classifiers were developed and compared for each color space and species separately. The discriminant functions developed using parameters selected using knowledge of the defect relationships determined using ANOVA outperformed those developed using randomly selected parameters, forward and backward selected parameters, and those which included all parameters, as shown in Table 4. The increase in classification accuracy due to the selection of proper classification variables demonstrates that having an in-depth knowledge of how parameters relate between defects allows the best possible classification functions to be developed.

The knowledge gained about defect parameter relationships can also be used to explain classification errors. Stain and mineral streak proved to be the cause of the majority of classification errors. The large number of parameters, which are not significantly different for stain and other defect classes, explain this error. Classification results indicate that for hardwoods, regardless of the colorspace, two color mean parameters were required for classification. Shape and density parameters were found to be poor classification variables when used alone, but increased the classification accuracy of a multi-parameter classifier by 5-15% indicating that multi-sensor information provides the best classification results.

4.2 Multi-Species

Next, a multi-species classifier was developed and compared using the same methods described above. The classifier developed provided better classification accuracy than classifiers with all or randomly selected parameters. The parameters selected for the multi species classifier were selected based on significant differences between defect classes. A multi-species classifier provides the greatest accuracy when two color mean parameters, one color standard variation parameter, a shape, and density parameter are used. When statistically comparing classification accuracies, single species classifiers were equal to, or out performed the multi-species classifier for each species.

4.3 Color Space Comparisons

Discriminant classifiers for each color

Table 4. RGB and HSI color based classification accuracies where F is the forward method, B is the backward method, A is all parameters, and S for parameters selected from parameter relationships.

Color Space	Species	Variables Selected	Defect Classification (% classified correct)			
			Barkpocket	Clearwood	Knot	Stain/Mineral
RGB	Red Oak	F	100	95	85	100
		B	90	95	90	89.5
		A	95	95	90	94.7
		S	95	100	95	100
	Hard Maple	F	100	95	95	88
		B	100	95	95	93
		A	100	95	95	81.25
		S	100	95	100	94
	White Pine	F	0	95	100	84.6
		B	78	95	100	84.6
		A	0	95	100	84.6
		S	100	100	100	92
HSI	Red Oak	F & B	90	95	75	94
		A	85	95	75	89.5
		S	90	100	90	100
	Hard Maple	F & B	100	95	95	93.7
		A	100	100	95	87.5
		S	100	95	95	100
	White Pine	F	77.8	100	95	100
		B	77.8	100	95	100
		A	0	95	90	76.9
		S	100	100	100	100

space, developed in the previous section, were compared to determine if the RGB and HSI color spaces provided significantly different classification results. Classification results were statistically compared and it was found that the two color spaces do not provide significantly different classification results. Next, two classification functions were developed and compared for each color space using color parameters only. It was again determined that there is not significant differences in the classification accuracy of the two color spaces as shown in Table 5.

Table 5. Classification results between color spaces using color parameters only.

Species	Color Space	Defect Classification (% classified correctly)				
		Barkpocket	Clearwood	Knot	Stain/Mineral	Overall
Red Oak	RGB	100	95	90	84.2	92.3
	HSI	90	100	85	78.6	88.4
Hard Maple	RGB	100	95	100	93	97.0
	HSI	92.8	95	100	100	97.0
White Pine	RGB	100	100	95	84.6	94.9
	HSI	100	100	95	76.9	93.0

3. Conclusions

The relationships of parameters between lumber defects were analyzed using statistical analysis. By characterizing significant differences between defects, those parameters that could be used to differentiate defects were selected. Both standard deviation and mean parameters should be used in defect differentiation. The parameters selected for each species were presented in Table 3. No significant differences were found between the resolutions of regional parameters in any of the defects; therefore, halving the resolution for the defects compared does not affect their parameter variability or relationships.

For different species, the I_m of defects was shown to relate to the I_m of clearwood. The ability to explain classification errors using the knowledge gained about defect parameters was demonstrated.

Classifiers developed using the knowledge of defect parameter relationships were found to provide higher feature classification accuracies for all features and species than those which used all parameters and where variable selection procedures has been used. This result suggests that by understanding how defects in lumber are represented by color, shape, and density parameters, the best possible classification can be achieved. For best results classification methods should include two color mean parameters, one color standard deviation parameter, a density parameter, and a shape parameter. Classification results indicate that for differentiating between difficult to classify defects and species color parameters provide improved classification. As suggested by Conners et al [9], Maristany et al.[10], two color parameters are required for the optimal classification accuracy of defects.

The authors found that combining parameters collected using multiple sensors increased the classification accuracy of wood defects in lumber. While density and shape parameters proved to be poor classifiers when used alone, combined with other parameters they both increase the performance of classifiers regardless of the species or colorspace. Although the conclusions are based on manually selected regions from homogeneous defect classes, the methods used to develop parameter relationships in this research can be used to increase the performance of classification methods for other defect types, species, and parameters.

3. References

[1] Szymani, R and K. A. McDonald. 1981. defect detection in lumber: state of the art. Forest Products Journal, 31(11):34-43.

[2] Portala, J. F. and J. Ciccotelli. 1992. Nondestructive testing techniques applied to wood scanning. Industrial Metrology, 2(3/4):299-307.

[3] Conners, R. W., T. H. Cho, C. T. Ng, T. H. Drayer, P. A. Araman; and R L. Brisbin. 1992. A machine vision system for automatically grading hardwood lumber. Industrial Metrology, 2(3/4):317-342.

[4] Åstrand, E. 1992. Detection and classification of surface defects in wood: A preliminary study. Department of Electrical Engineering, Linkoping University, LiTH-ISY-I-1437.

[5] Hagman, P. O. G. and S. Grundberg. 1993. Multivariate image analysis methods to classify features on Scots Pine: evaluation of a multi-sensor approach. In: R. Szymani (ed.) 5th International Conference on Scanning Technology and Process Control for the Wood Products Industry, October 25-27, 1993, Atlanta, Georgia. 18 p.

[6] Kline, D. E., R. W. Conners, D. L. Schmoldt, P. A. Araman, and R. L. Brisbin. 1993. A multiple sensor machine vision system for automatic hardwood feature detection. In: R. Szymani (Ed.) 5th International Conference on Scanning Technology& Process Control for the Wood Industry, October 25-27, 1993, Atlanta, Georgia, 11 p.

[7] Conners, R. W., D. E. Kline, P. A. Araman, and T. H. Drayer. 1997. Machine Vision Technology for the Forest Products Industry. IEEE Computer Innovative Technology for

Computer Professionals 30(7):43-48.

[8] Bond, B. H. 1998. Characterization of Wood Features Using Color, Shape, and Density Parameters. Dissertation. Virginia Polytechnic Institute and State University. Blacksburg, Va.

[9] Conners, R W., C. W. McMillin, and C. N. Ng. 1985. The utility of color information in the location and identification of defects in surfaced hardwood lumber. Proceedings, 1st International Conference on Scanning Technology in Sawmilling, San Francisco, California, pp. XVIII-I to XVIII-33.

[10] Maristany, A. G., D.A. Butler, Brunner, C. C., and J. W. Funck. 1991. Exploiting Local Color Information for Defect Detection on Douglas-Fir Veneer. 4th International Conference on Scanning Technology in the Wood Industry. October 28-29, 1991. Curlingame, California.

PROCEEDINGS OF THE INTERNATIONAL CONFERENCE ON MULTISOURCE-MULTISENSOR INFORMATION FUSION

FUSION'98

Volume II

Editors:

Hamid R. Arabnia & Dongping (Daniel) Zhu

Associate Editors:

O. Aboutalib, M. Bedworth, E. Blasch, C. Bowman, D. D. Bustamante, N. Chen, B. V. Dasarathy, U. Degen, O. E. Drummond, C. Harris, D. Huang, Z. Jing, I. Kadar, J. Llinas, D. B. Malkoff, A. L. Meyrowitz, H. Pan, J. Qian, N. S. V. Rao, D. Schmoldt, B. Solaiman, P. Svensson, P. K. Varshney, Y. Wang, Z-T Wang, L. Webster, & J. Williams

Las Vegas, Nevada, USA
July 6 - 9, 1998
CSREA Press