ARTICLE IN PRESS

Computers and Electronics in Agriculture xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Validation of automated hardwood lumber grading system

Rado Gazo[a,*], Logan Wells[a], Vojtech Krs[b], Bedrich Benes[b]

[a] Department of Forestry and Natural Resources, Purdue University, United States
[b] Department of Computer Graphics and Programing, Purdue University, United States

ARTICLE INFO

Keywords:
Automated
Hardwood
Lumber
Grading
Scanning
NHLA

ABSTRACT

Grading is one of the most vital steps in the hardwood lumber manufacturing process. For over one hundred years, hardwood lumber in North America has been graded by specially trained lumber inspectors using the National Hardwood Lumber Association (NHLA) Rules for the Inspection of Hardwood Lumber. With technology improving over time, the status quo of lumber grading is again being challenged. This paper outlines an automated lumber grading study using a Microtec Goldeneye 300 Multi-Sensor Quality Scanner™. The scanner is equipped with color cameras, dot-grid and profile lasers and an x-ray sensor to locate and classify defects at a speed of 980 linear feet per minute. The material studied was rough, kiln dried hardwood lumber of nine different commercial species. Over 1000 boards from each species were graded with the scanner and verified by a NHLA-trained human lumber inspector. This paper reviews the performance of the scanner and highlights its accuracy by species and individual grades within that species. Across the entire volume of boards scanned, the automated grading system was 99.50% on-value and 92.22% on-grade accurate.

1. Introduction

Sawmills must continue to strive to be more efficient for two reasons, (1) to stay in business and remain profitable and (2) to be as responsible with timber resources as possible. Any process that does not utilize material to its fullest potential is wasteful and becomes a burden to business in an effort to maximize the value of every piece of lumber (Araman et al., 1992, Kline et al., 2003, Bhandarkar et al., 2008). On the wholesale market, the value of lumber is determined by many factors including but not limited to the tree species, region of origin, board thickness, average width, moisture content and the board's quality grade. Hardwood lumber in the North America is graded in accordance to the National Hardwood Lumber Association (NHLA) Rules for hardwood lumber inspection (NHLA, 2015). The standard rules for grading hardwood lumber assign a grade to a board based on the amount of clear wood available by a limited number of cuttings of a minimum size. Currently hardwood lumber is graded manually by identifying the board's dimensions, defects and calculating the size of clear areas, or cuttings, in the piece of lumber. In theory, one may expect a properly trained and experienced lumber grader to be 100% accurate. In a real production environment, however, that same grader, averaged over an entire shift, week, or month will not perform at their best all of the time. It has been documented in multiple studies that the average accuracy of a human lumber inspector can be as low as 48% to as high as 75% (Huber et al., 1985, Kline et al., 2003, Pham and Alcock, 1998). Speed of production line, challenging mental calculations, difficulty of identifying all lumber features in long lumber by a single inspector, working conditions and fatigue from monotone repetitive task all contribute to reduced accuracy. From an accuracy standpoint, automation could greatly improve the industry's grading efficiency (Conners et al., 1989, Araman et al., 1992).

In the early 1980s, the United States Forest Service (USFS), in cooperation with researchers at Louisiana State University (LSU) and Virginia Polytechnic Institute and State University (Virginia Tech), envisioned a fully automated hardwood industry using an Automated Lumber Processing System (ALPS). Everything from log sawing patterns to grading the final boards would be done by computer automation (McMillin et al., 1984). The biggest challenges included the shortage of computer processing capability, data storage capacity and scanner sensor accuracy needed to grade boards automatically. Klinkhachorn and colleagues developed an improved computer program to grade virtual boards, but still lacked the adequate data collection capabilities of an accurate scanner (Klinkhachorn et al., 1987). In partnership with the United States Forest Service (USFS), Virginia Tech researchers developed an improved machine vision system used to identify lumber defects (Conners et al., 1989, Cho et al., 1990a). The majority of machine vision research focused on surfaced hardwood lumber utilizing color cameras and image shapes to identify defects (Conners et al.,

* Corresponding author.
E-mail address: gazo@purdue.edu (R. Gazo).

https://doi.org/10.1016/j.compag.2018.06.041
Received 17 April 2018; Received in revised form 20 June 2018; Accepted 25 June 2018

1989, Cho et al., 1990b). Other types of defect detecting technology included laser, X-ray, microwave, ultrasonic and neutron methods (Pham and Alcock, 1998). Research continued to improve the accuracy of defect detection in lumber scanning, but there were still issues with false positive errors, or detecting defects that did not exist (Kline et al., 1998). To help reduce false positives and greatly increase scanning defect detection accuracy, Bond et al. (2007) and Kline et al. (2003) used an integrated sensor approach. They demonstrated a significant statistical increase in grading accuracy using a combination of sensors including not only color cameras, but also shape measurements and X-ray density values (Bond, 1998, Bond et al., 2007). Kline et al. (2003) used this same multi-sensor approach to feed scanned images into improved lumber grading computer algorithms. The multi sensor approach increased the accuracy of defect detection and resulting grading accuracy in Kline's study to 63% while scanning 89 boards at 120 lineal feet/min (36 m/min).

During the mid-2000s, multi sensor lumber scanners started to be commercially accepted by industry. Multiple companies began to sell lumber scanners used primarily for crosscut optimization in rough mills to cut out defects from lumber efficiently and accurately. Buehlmann conducted a study using surfaced and kiln dried yellow birch to compare the defect detection capabilities of four different commercial scanners, demonstrating an improved accuracy over previous non-commercial prototype scanners (2007). Lumber grading software continued to improve and be utilized in sawing optimization research using computed tomography (CT) log scanning (Bhandarkar et al., 2008, Chang and Gazo, 2009). Today, with more powerful computers, higher quality cameras and more precise sensors, it is now feasible to revisit the Forest Service's vision to combine automatic defect detection from a scanner with lumber grading software and applying it to an industrial scale.

1.1. Objective

The objective of this study was to conduct a large-scale validation of the automated hardwood lumber grading system in an industrial setting by analyzing 1000 boards of each of the nine selected hardwood species.

2. Methods and materials

2.1. Equipment

A 2014 Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ was used to identify and classify defects in lumber. This scanner uses color scanning, X-ray scanning, 3D laser triangulation, laser scattering and grain deviation detection to find defects on each face of the board. Data from all sensors are correlated to increase accuracy of defect detection and minimize false positive errors. The scanner ran at approximately 980 feet/min (300 m/min).

2.2. Sensors

Color cameras are the main sensors used in lumber scanners. They allow for accurate identification of color changes on the surfaces of the board. Thresholds are set to identify the contrast between clear wood, knots, stains and other defects. These cameras, however, will also pick up unwanted visual signals such as a boot print, dirt smudge or conveyer mark.

Black and white scatter cameras are used in conjunction with the line and dot grid lasers. The shape of the laser light will change based on how it refracts against the wood cells (Jolma and Mäkynen, 2007). The black and white scatter camera determines the movement of the grain or fiber deviation and maps out grain patterns near knots. Because wood grain deviates from straight direction around knots and other defects, but it does not around the dirt or conveyer mark, combining these two sensors helps eliminating detection of unwanted features.

The 3D profile camera is used in accordance with the scanner's lasers to look at not only the shape of the board and locate wane, but also to verify cracks and holes that might confuse the scanner's vertical camera perspectives.

Finally, the X-ray is one of the most vital sensors on the scanner, used to map the density of a board. Knots, for example, have higher density than clear wood, where a hole or lack of material would comparatively have very little or no density. All the sensors work together to verify different defects and gather information about the board. By setting thresholds for different defects on each type of sensor and overlapping each sensor's data, false defects can be filtered out and only the true defects are identified and classified. A detailed description of defect types, defect detection and accuracy of defect detection and identification by type is given in accompanying paper (COMPAG_2018_578) by Wells et al. (2018).

2.3. Calibration

Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ is typically used to scan surfaced or skip surfaced, uniform-width strips of kiln dried lumber in rough mills. For this test, input material was rough sawn, unsurfaced, random-width, kiln dried lumber of nine common hardwood species – ash, basswood, cherry, hard maple, hickory, red oak, soft maple, white oak and yellow poplar. Scanning of the rough lumber (Conners et al., 1992) is a prominent concern because dirty and coarse surfaces of the board can cause confusion to scanner sensors. Substantial effort was put into calibration of defect detection in rough lumber by Microtec engineers along with a NHLA trained grader (Del Re, 2018).

2.4. Hardwood lumber grading software

Gazo and Benes (2013) and Gazo et al. (2014) developed software, LogView™, to visualize, identify and classify internal features in data from CT scanning of logs. In addition, LogView™ optimizes processing of hardwood logs into veneer or lumber by simulating and evaluating all processing parameters based on knowledge of internal features of logs. An integral part of this process is virtual grading of boards and veneer anytime a processing parameter is changed. This is accomplished by GradeView™, a grading algorithm developed by Gazo et al. (2014) that is capable of rapidly evaluating quality of boards based on NHLA grading rules, as well as custom-defined rules.

2.5. Sample material

During normal sawmill operation, lumber exiting dry kilns is brought to a grading line where it is graded, upgraded by trimming if necessary, sorted by species, grade and length, tallied, stacked, packaged for shipment and stored in a warehouse prior to shipping out. The sample boards for the testing came from packages that were previously graded by NHLA trained graders, tallied and ready to be shipped out.

For the study, nine different species of lumber were used- ash, basswood, cherry, hard maple, hickory, red oak, soft maple, white oak and yellow poplar. Over one thousand boards of each of these species were scanned to provide a large enough sample size and demonstrate that automated lumber grading could be done on a production scale. NHLA rules define six grades – First and Seconds (FAS), FAS one Face (F1F), SELECTS (SEL), #1 Common (1C), #2 Common and #3 Common. #2 and #3 Common grades can be either Clear (2A, 3A) or Sound (2B, 3B). Many mills group 2A and 2B into a single grade of #2 Common (2C) and similarly 3A and 3B into #3 Common (3C). Additionally, it is a common commercial practice to group 3 top grades of FAS, F1F and SEL together as a single grade Selects & Better (Sel& Btr).

In this study, equal amounts, approximately 300–350 boards, of

Table 1
Number of boards analyzed by species and grade.

Type	Total	Sel&Btr	1C	2C
Ash	1016	345	315	356
Basswood	1023	259	511	253
Cherry	1095	324	596	202
Hard Maple	1074	404	367	303
Hickory	1021	305	414	302
Red Oak	1065	247	424	394
Soft Maple	1038	315	257	466
White Oak	1098	293	577	228
Yellow Poplar	1024	337	408	279
All Species	9454	2829	3842	2783

Table 2
Board feet of lumber analyzed by species and grade.

Type	Total	Sel&Btr	1C	2C
Ash	4089	1418	1275	1333
Basswood	4037	1127	1911	999
Cherry	4130	1435	1944	751
Hard Maple	5836	2181	2003	1652
Hickory	3964	1211	1326	1427
Red Oak	4108	1228	1513	1367
Soft Maple	5531	1416	1131	2984
White Oak	3910	1392	1845	673
Yellow Poplar	4289	1733	1429	1127
All Species	39,894	13,204	14,377	12,313

each of the three main grade categories- Sel&Btr, 1C and 2C were used. Due to research taking place at an active sawmill, the study had to work with the available inventory. To maintain consistency and for ease of manual material handling, the thickness of lumber was limited to 4/4 and 5/4 of inches. The sample size of scanned boards by species and by grade is described in Table 1 (by number) and Table 2 (by volume). The total comprised approximately 100 packages of lumber, averaging about 400 BF per pack.

2.6. Procedure

At the beginning of 2017, Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ and GradeView™ algorithm were integrated into the Automated Hardwood Lumber Grading System and installed off-line in a medium-sized Midwestern hardwood sawmill.

Over a period of three months, approximately 100 packages of lumber were scanned and graded. During the first pass, the boards for which previously human-assigned grade matched the scanner grade, were set aside and considered successfully graded. The boards that did not match the human-assigned grade were then scanned one more time and inspected in detail in the presence of a trained lumber grader. Some of these boards were graded correctly by the original human grader and some were graded correctly by the scanner. The way in which sensors are used either individually or in combination, and the detection algorithms that are used to detect specific defects in each wood species have a great effect on defect identification accuracy. In each case, the reason for discrepancy was recorded. Table 3 shows the reasons for miss-grading a board by the scanner and the number of times a board was graded incorrectly as a result of that. This data is presented here in order to point out the areas in which the scanning technology can be further improved. We offer a detailed analysis of data presented in Table 3 in a companion paper (possible citation here).

2.7. Limitations

Physical lumber feeding mechanism limitations of test setup allowed boards up to 9.5” wide, 4” thick and 12’ long to be scanned. Since surface defect detection and identification is not affected by the length and width of a board, this should have no effect on grading accuracy.

All previous studies used a limited sample size, for example, Kline et al. (2003) used 89 boards. Due to our objective of testing a large sample of 9454 boards (39,894 board feet), it was not feasible to re-inspect all boards for which human grade and scanner grade both agreed. In cases when both board grades were the same, the grade was assumed to be correct and no further action was taken. During 2 days of the study, the NHLA Chief Lumber Inspector and Dean of Inspector Training School was in attendance to verify grading of the boards. During his presence, all boards, including those for which human grade and scanner grade both agreed, were re-inspected. This amounted to 282 boards (1080 board feet) of red oak, 368 boards (1345 board feet) of white oak, and 208 boards (946 board feet) of ash. The on-value and on-grade accuracy for these boards was 99.48% and 91.11% respectively for red oak, 99.87% and 95.83% respectively for white oak and 96.03% on-value and 86.68% on-grade respectively for ash. These subsample results are consistent with our overall results. While it is conceivable that some of these boards could have been miss-graded by both human and the scanner we believe that occurrence of this was minimal. Therefore, we feel that this approach was justified in order to analyze much larger sample size.

3. Results

The on-value and on-grade performance of the automated hardwood lumber grading system was calculated by comparing scanner grade to true grade. Scanner grade is the grade assigned to each board by the scanner. True grade is the previously human-assigned grade if the original human grade was correct. If the human and scanner grades were not the same, then the inspector-assigned grade is the true grade.

On-value and on-grade performance was calculated for the entire sample size, by species, by species and grade and by each individual package of lumber. The value was then averaged for all packages within the same species/grade combination. If on-value accuracy is less than 100%, it means that scanner under-valued that sample. Accuracy over 100% means that scanner over-valued the sample. On-grade accuracy is always less than 100% and is calculated on board foot volume basis.

While we do have on-grade and on-value accuracy for each bundle, these are not included here for two reasons: (1) the size of the resulting table would far exceed its value for this paper and (2) because any accuracy disputes between lumber buyer and seller are based off the total invoice, which, in fact, can include many items, it seems more generally informative here to list accuracy by species and grade.

After grading the 9454 boards (39,894 board feet), the overall on-value scanner accuracy was 99.54% an on-grade accuracy was 92.22%. Detailed results are given in Tables 4 and 5.

4. Discussion

The NHLA Sales Code states that when selling lumber, the board footage of the lumber shipment as listed on the invoice must meet two requirements. First, the true value of the lumber shipped must be within 4% of the invoice value (i.e. minimum 96% on-value accuracy). Second, at least 80% of the board footage shipped must be the correct grade, minimum on-grade accuracy (NHLA, 2015). To calculate the value of each board, the lumber price listed in the Feb 1, 2017 Hardwood Market Report from the Appalachian lumber region for each species (HMR, 2017) was used.

4.1. On-value accuracy

The overall on-value accuracy of 99.54%, as well as the average on-value accuracy for each species, was far better than the 4% margin of error that NHLA rules allow. The on-value accuracy of two higher grades, Sel&Btr and 1C, for all species was also better than the 4%

Table 3
Reasons and frequency of miss-grading a board by scanner.

Species	Iron Stain	Large Knot	False Knot	Black Knots 1/4″ or less	Surface Roughness	Wormholes	Shake	Rot	Pith	False Mineral	Glassworm	Cluster Knots 1/8″ or less	Total
Ash	18	19	2	25	1	0	1	24	8	0	5	0	103
Basswood	18	0	5	22	8	3	0	0	3	2	0	0	61
Cherry	7	5	24	3	6	5	3	4	9	1	0	3	70
Hard Maple	11	36	2	11	2	2	3	0	5	0	0	0	72
Hickory	2	12	17	4	11	0	11	0	2	2	0	0	61
Red Oak	34	6	8	3	20	14	6	0	0	3	0	0	94
Soft Maple	14	24	17	10	5	12	2	0	1	1	0	0	86
White Oak	91	6	5	5	10	4	1	0	0	1	0	0	123
Y. Poplar	3	2	26	10	5	0	3	1	1	3	0	1	55
Total	198	110	106	93	68	40	30	29	29	13	5	4	725

Table 4
On-value scanner accuracy by species and grade.

Species	Overall	Sel&Btr	1C	2C
Ash	99.31%	98.79%	103.02%	102.81%
Basswood	98.77%	97.54%	100.25%	111.90%
Cherry	100.03%	98.33%	99.76%	107.84%
Hard Maple	97.64%	98.77%	103.38%	108.65%
Hickory	100.83%	96.57%	99.33%	102.41%
Red Oak	100.44%	98.83%	98.74%	102.39%
Soft Maple	100.00%	96.77%	101.62%	102.61%
White Oak	99.37%	100.41%	100.55%	101.83%
Yellow Poplar	100.32%	98.08%	99.99%	104.16%
All Species	99.54%			

Table 5
On-grade scanner accuracy by species and grade.

Species	Overall	Sel&Btr	1C	2C
Ash	89.41%	93.86%	89.18%	84.70%
Basswood	93.63%	94.85%	96.55%	86.69%
Cherry	92.74%	94.70%	92.13%	90.55%
Hard Maple	91.33%	98.26%	91.31%	82.20%
Hickory	91.90%	86.79%	97.51%	91.03%
Red Oak	89.34%	95.96%	93.49%	93.35%
Soft Maple	92.95%	90.96%	88.17%	89.17%
White Oak	94.32%	89.48%	89.39%	95.95%
Yellow Poplar	94.45%	95.47%	92.95%	95.69%
All Species	92.22%	93.82%	92.45%	90.23%

allowed margin of error.

For four out of the nine species, the on-value accuracy of 2C grade slightly exceeded the 4% margin of error. Being a lower grade, 2C lumber has more defects and less clear wood. That means that there is a greater chance of the scanner missing or wrongly identifying a defect, thus assigning a higher value to the lumber. Moreover, some of these were low board-count packages compared to average. Basswood and cherry 2C lumber groups were two of the smallest sample sizes. Only 253 boards (999 board feet) of 2C basswood was scanned and 202 boards (751 board feet) of 2C cherry lumber. Small sample sizes were a result of limited availability in mill inventory.

A special note must be made regarding the Sel&Btr grade in white oak being overvalued. It may seem counterintuitive that highest-value grade can be overvalued by a scanner, but this is caused by the fact that there were lower grade boards in those packages (reducing true value of the package) and scanner graded those boards as the higher grade. White oak is different from other species due to an iron stain, a stain that develops when green lumber that is not dipped in anti-stain solution comes in contact with iron. Some mills experience it and some do not, while others experience it seasonally. The scanner does not get confused with iron stain until it becomes severe. In such cases, the scanner grading solution for white oak was adjusted to account for severe iron stain.

4.2. *On-grade accuracy*

The overall on-grade accuracy of 92.22%, as well as the average on-value accuracy for each species, and species/grade combination was better than the 80% minimum accuracy called for by the NHLA Sales Code. As mentioned previously, published studies of human graders report accuracy between 48 and 75%.

4.3. *Future considerations*

Some important commercial species considerations of hardwood lumber were left out of this study. First, and most obvious, is the absence of scanning black walnut lumber. While lumber scanners made rapid progress over the last decade in terms of speed, ability to scan rough lumber, number of species that can be detected, etc., this study was not able to calibrate the 2014 Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ to identify defects in black walnut to achieve satisfactory performance. This is mainly due to the similar density and dark color of both the clear wood and large knots.

Since the scanner had been built in 2014, several sensor improvements became available in lumber scanning. For hardwood lumber specifically, the use of lasers in the non-visible spectrum significantly improves detection of knots and grain deviation (Del Re, 2018).

An important consideration of future work is to look at different color requirements for species specific rules, for example #1 White and #2 White hard maple color sorts. This study did not use color sorting for grading maple, just standard grading rules. It would be possible to calculate cuttings without brown heartwood with the scanner used in this study, but due to time and budget constraints those factors were not evaluated.

In addition to increasing the accuracy and speed of hardwood lumber grading, the automated hardwood lumber scanning system can provide other benefits. A human grader's ability to recognize boards that can be re-manufactured to increase their value is vital to the success of a mill. When a major grading defect is located near the end or an edge of the board, it is a common practice to remanufacture such board by trimming the end(s) to length or ripping to width. Such practice results in a board that is smaller, but more valuable. The automated solution can provide superior benefits in this regard compared to a human grader. The potential for optimizing the grade of every individual board might be even more important than the increased production efficiencies of the scanner.

5. Conclusions

The presented hardwood lumber grading system consisted of the Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ for defect detection and classification, and the GradeView™ grading algorithm for determining NHLA lumber grades. After scanning and grading of 9454 boards (39,894 board feet) of nine commercially important hardwood species at the scanner speed of 980 lineal feet/minute, the overall on-value scanner accuracy was 99.54% an on-grade accuracy was 92.22%, far exceeding industry standards of 96% and 80%, respectively, thus validating the system. The scanner errors can be further decreased by improved defect detection, an effort that is currently under way.

The Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ is a longitudinal- feed scanner.capable of running at speeds of up 3000 lineal feet per minute. Our test speed of 980 lineal feet per minute was calculated to be sufficient for a sawmill with annual production of approximately 20–25 million board feet of lumber. If higher through put or material flow logistics dictate the use of transverse-feed scanner, Microtec Goldeneye Plus Scanner™ scanner can be used with the same results.

Acknowledgements

This study was partially funded by National Institute for Food and Agriculture and Indiana Next Generation Manufacturing Competitiveness Center. In-kind contributions in form of lumber, personnel and equipment were provided by Pike Lumber Company and Microtec, GmbH.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.compag.2018.06.041.

References

Araman, P.A., Schmoldt, D.L., Cho, T.H., Zhu, D., Conners, R.W., Kline, D.E., 1992. Machine vision systems for processing hardwood lumber and logs. AI Appl. 6 (2), 13–26.

Bhandarkar, S.M., Luo, X., Daniels, R.F., Tollner, E.W., 2008. Automated planning and optimization of lumber production using machine vision and computed tomography. IEEE Trans. Automat. Sci. Eng. 5 (4), 677–695.

Kline, D.E., Surak, C., Araman, P.A., 2003. Automated hardwood lumber grading utilizing a multiple sensor machine vision technology. Comput. Electron. Agric. 41 (1–3), 139–155. https://doi.org/10.1016/S0168-1699(03)00048-6.

National Hardwood Lumber Association, 2015. Rules for the Measurement and Inspection of Hardwood and Cypress Lumber. NHLA, Memphis, TN, pp. 20–21.

Huber, H.A., McMillin, C.W., McKinney, J.P., 1985. Lumber defect detection abilities of furniture rough mill employees. Forest Products J. 35 (11/12), 79–82.

Pham, D.T., Alcock, R.J., 1998. Automated grading and defect detection: a review. Forest Products J. 48 (4), 34–42.

Conners, R.W., Ng, C.T., Cho, T.H., McMillin, C.W. 1989. Computer vision system for locating and identifying defects in hardwood lumber. In: Proc. SPIE 1095, Applications of Artificial Intelligence VII. pp. 48–63. doi:10.1117/12.969258.

McMillin, C.W., Conners, R.W., Huber, H.A., 1984. ALPS: a potential new automated lumber processing system. Retrieved from. Forest Products J. 34 (1), 13–20. http://cat.inist.fr/?aModele=afficheN&cpsidt=9426282.

Klinkhachorn, P., Franklin, J.P., McMillin, C.W., Conners, R.W., Huber, H.A., 1987. Automated computer grading of hardwood lumber. Forest Products J. 38 (February 1987), 67–69.

Cho, T.H., Conners, R.W., Araman, P.A., 1990a. A computer vision system for analyzing images of rough hardwood lumber. In: Pattern Recognition, 1990. Proceedings., 10th International Conference on, vol. 1. IEEE, pp. 726–728.

Cho, T.H., Conners, R.W., Araman, P.A., 1990b. A computer vision system for automated grading of rough hardwood lumber using a knowledge-based approach. In: Systems, Man and Cybernetics, 1990. Conference Proceedings., IEEE International Conference on. IEEE, pp. 345–350.

Kline, D.E., Widoyoko, A., Wiedenbeck, J.K., Araman, P.A., 1998. Performance of color camera machine vision in automated furniture rough mill systems. Forest Products J. 48 (3), 38.

Bond, B.H., Kline, D.E., Araman, P.A., 2007. Differentiating defects in red oak lumber by discriminant analysis using color, shape, and density. Wood Fiber Sci. 34 (4), 516–528.

Bond, B.H., 1998. Characterization of Wood Features Using Color, Shape, and Density Parameters. Doctoral Dissertation, Virginia Tech. 1998.

Buehlmann, U., Lihra, T., Rancourt, V., Ait-Kadi, D., 2007. Detection capabilities of automated hardwood lumber defect-detection systems. Forest Products J. 57 (10), 51–57 Retrieved from < Go to ISI > ://WOS:000250491800007.

Chang, J., Gazo, R., 2009. Measuring the effect of internal log defect scanning on the value of lumber produced. Forest Products J 59 (11/12), 56–59.

Jolma, I.P., Mäkynen, A.J., 2007. The detection of knots in wood materials using the tracheid effect. In: Advanced Laser Technologies 2007. International Society for Optics and Photonics. pp. 70220G-70220G.

Conners, R.W., Cho, T., Ng, C.T., Drayer, T.H., Brisbin, R.L., 1992. A machine vision system for automatically grading hardwood lumber. Ind. Metrol. 2, 317–342.

Del Re, Ricardo., 2018. [Telephone interview]. Instalment Engineer, Springer Microtec Inc.

Gazo, R., Benes, B., 2013. Computed tomography log scanning: an industrial application. In: Proceedings of ISCHP 2013 – 4th International Scientific Conference on Hardwood Processing. Florence, Italy. pp. 140–147.

Gazo, R., Vanek, J., Abdul-Massih, M., Benes, B., 2014. CT scanning of logs – analysis and optimization for better utilization of hardwoods. In: Proceedings of Society of Wood Science and Technology 2014 International Convention - Sustainable Resources and Technology for Forest Products. Zvolen, Slovakia.

Hardwood Market Report. 2017. Appalachian Kiln Dried Net Tally Prices. Vol. XCV Number 5. pp. 8–9.