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

Original papers

Defect detection performance of automated hardwood lumber grading system

Logan Wells[a], Rado Gazo[a,*], Riccardo Del Re[b], Vojtech Krs[c], Bedrich Benes[c]

[a] Dept. of Forestry and Natural Resources, Purdue University, USA
[b] Springer Microtec Inc, Italy
[c] Department of Computer Graphics and Programing, Purdue University, USA

ARTICLE INFO

Keywords:
Hardwood
Lumber
NHLA
Grading
Defect
Detection

ABSTRACT

This paper describes the abilities of the Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ to recognize and identify defects for purpose of grading kiln dried, rough, hardwood lumber using the GradeView™ grading algorithm. The overall accuracy of the automated grading system was found to be 92.22% on grade and 99.50% on value as defined by the National Hardwood Lumber Association sales code, well within industry standards. We also discuss the small number of boards that were graded incorrectly by the system and specifically how the multi sensor scanner detects various lumber defects. This scanner has six different types of sensors-color cameras, black and white cameras, profile cameras, line lasers, dot lasers and an X-ray that work together to provide accurate detail for lumber grading.

1. Introduction

During the spring of 2017, a study was conducted to test the feasibility of an automated hardwood lumber grading system. This system integrated the GradeView™ lumber grading computer algorithm and the Microtec Goldeneye 300 Multi-Sensor Quality Scanner™. Building upon initial 2015 tests performed at Stiles Machinery in High Point, North Carolina as a proof of concept study, this study analyzed 9454 kiln dried, random width, rough boards in a Midwestern grade hardwood sawmill. More than 1000 boards from nine different commercial hardwood species- ash, basswood, cherry, hard maple, hickory, red oak, soft maple, white oak and yellow poplar- were scanned and graded. The overall on-grade accuracy of the automated lumber grading system was 92.2% (Gazo et al., 2018). The on-value accuracy of the study showed that the value of the total lumber scanned was 99.5% of the true human verified lumber value. Both of these measures are well within the National Hardwood Lumber Association (NHLA) Sales Code requirements of at least 80% on-grade accuracy and 96% on-value and indicate that this system is ready to be commercialized and adopted by industry.

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).

Automated hardwood lumber grading was first introduced by the US Forest Service in 1983 as part of an Automated Lumber Processing System (McMillin et al., 1984). Automated grading is broken into two parts: first locating and identifying types of defects; second interpreting the defect and board data with a software to determine the board grade (Klinkhachorn et al., 1987). 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, Virginia Tech researchers developed an improved machine vision system used to identify lumber defects (Conners et al., 1989, Cho et al., 1990a) by scanning surfaced hardwood lumber utilizing color cameras and image shapes to identify defects (Conners et al., 1989, Cho et al., 1990b).

The computer algorithm interprets the defects and clear wood to assign a lumber grade and value to the board. This computer code can

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

https://doi.org/10.1016/j.compag.2018.09.025
Received 25 April 2018; Received in revised form 6 September 2018; Accepted 20 September 2018

be based directly off the NHLA lumber grading rules or proprietary grades from a specific company's standards. The grading computer code is a significant accomplishment and the computing power to run the algorithm was once a monumental challenge to this process. With the advances in computing power, the software component of automated lumber grading has been well established and used not only to grade lumber but assist in entire log sawing optimization (Bhandarkar et al., 2008, Chang and Gazo, 2009). Locating and determining defects in a board is the more challenging component in hardwood lumber grading because of the subjectivity in defining what is and what is not a defect. Gathering defect data with machine vision technology is difficult for multiple reasons, but all these start with the fact that wood is a natural, biological material.

Wood is not a homogenous material; every piece of lumber is different. Between species, and within a single species, there can be hundreds of different features and colors that are allowable as clear wood for grading purposes. Besides the inherent variability in wood, there is also the coarseness of rough lumber. The fibrous nature of wood and vibrating saw kerf in manufacturing creates a rough surface that has been described as the rough lumber problem (Conners et al., 1992). There is a fine balance between enough detail to determine clear wood from defects and creating too much noise or false positive defects from the rough surface. Color cameras and other sensors that identify defects have advanced greatly in the last 30 years to improve this surface roughness detection balance.

Because the coarseness of rough lumber was such a barrier to early sensors, most of the early machine vision studies worked with surfaced lumber. Setting thresholds of defect colors at the individual pixel level of camera imaging was one of the foundational steps in defect detection. Early researchers established a pixel histogram threshold technique that continues to be the base of color camera detection today (Conners et al., 1983, McMillin et al., 1984, Cho et al., 1990a, Kline et al., 2003). Another established feature was looking at the shape of defects (Conners et al., 1989, Cho et al., 1990b). For example, if the pixels are in a shape that is more long than wide, the defect is more likely to be a split than a knot. In addition to color cameras, other sensors such as lasers, x-ray, microwave, ultrasonic and neutron methods (Pham and Alcock, 1998) have been tested. Each type of sensor has certain strengths and weaknesses. While research and development of sensors advanced, the detection of false positives, or detection of features that were not actually defects, continued to be a problem (Kline et al., 1998). To help reduce false positives and greatly increase scanning detection accuracy, Bond et al. (2002) 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 et al., 2002). 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/minute (36 m/minute).

During the mid 2000's, commercial scanners used for identifying defects in cross-cut optimization applications became readily available on the market. Buehlmann et al. (2007) did a thorough analysis of the detection capabilities with four different industrial scanners. The fully automated machine vision capabilities of the different scanners were tested by scanning eleven different dried and surfaced yellow birch sample boards that contained different types of lumber defects. The results of the study showed a clear difference in the detection capabilities of scanners based on their cost, which is directly related to the number and types of sensors used in the scanner. Certain defects were still a challenge to be detected, including pin knots, individual worm holes, shake and white speck, a decay fungi. Other defects such as shake, mineral streak and stains were detected, but only partially. While detection was not perfect with any of tested automated scanning systems, they were still sufficiently accurate to be used by industry (Buehlmann et al., 2007) on clean, surfaced, fixed-width strips of lumber.

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. While using scanners for cross cut optimizing has been readily adopted, grading kiln dried, random width, rough hardwood lumber has not gone through pilot scale tests to evaluate scanner performance until Gazo et al. (2018).

2. Objective

The purpose of this paper is to describe the ability of the Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ to locate and identify defects in kiln dried, rough hardwood lumber. Boards graded incorrectly by GradeView™ because of incorrect detection by the scanner will be the focus of this analysis. Gazo et al. (2018) demonstrated the accuracy of the scanner to be 92.2% on-grade overall, this analysis is focusing on the 7.8% that was graded incorrectly.

3. Methods

Boards were scanned with a Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ and the data was analyzed with the Purdue GradeView™ algorithm. Together these hardware and software components were combined to make an automated hardwood lumber grading system. The kiln dried, random width, rough hardwood lumber from nine different species- ash, basswood, cherry, hard maple, hickory, red oak, soft maple, white oak and yellow poplar- were scanned at 980 lineal feet per minute. Sensors looked at the top and bottom faces of the board at the same time and created a digital map of all the defects.

Over a period of three months, approximately 100 packages of lumber were scanned and graded. These packages of lumber had been graded and tallied by the host sawmill and were pulled from the inventory ready to be sold. During the first pass through the scanner, 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. In each case, the reason for discrepancy was recorded.

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. It is also used to measure board thickness differentially by a combination of 3D profile camera from different side views and generates a full thickness map imaging.

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 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 overlaying each sensor's data, false defects can be filtered out and only the true defects are identified and classified.

The geometric size and shape of a board is measured with line laser systems and profile camera laser triangulation. Board surface measure is calculated using the width of the board one-third the length from the narrow end just as the NHLA rules require. This differs from board width in that the board width is calculated from the narrowest width in the standard length of the board, over length not included. Any side bend or taper greater than 1/8th inch is accounted for with the geometric size calculations and cameras. Board cupping and bow was not measured with the test scanner because the feed rolls press down the board with a great amount of pressure to achieve accurate feeding. A commercial scanner of this type can include sensors for detecting cup and bow. Miss-cut lumber that varies in thickness can be detected using the laser triangulation.

Table 1 gives a summary of different sensor combinations to identify specific board features. Due to anatomical differences in wood of various species, the sensors have to be calibrated for each individual wood species in order to learn differences in density, color and shape of various defect types and clear wood. Substantial effort was put into calibration of defect detection in rough lumber by Microtec engineers along with a NHLA trained grader (Del Re, 2018). Because hardwood lumber is commonly graded in rough, unsurfaced condition, these calibration measures were critical to develop because of the coarseness of unsurfaced material being scanned.

4. Results

The purpose of the automated hardwood lumber grading systems is to detect defects with sufficient accuracy and detail to establish a defined grade of a board. The reasons why 7.8% of the board footage had not been assigned a correct grade vary. If the scanner did not find a defect in the board that was truly present this is called under detection. The grading algorithm would overestimate the amount of clear wood available by allowing the defect and surrounding wood to be placed into a clear cutting. A clear cutting is a section of a board obtained by crosscutting, ripping or both and free from defects (NHLA, 2015). These cuttings must be of a minimum size and only a certain number is allowed. The board grade is determined by percentage of the boards surface area can be used in these cuttings.

The next possible way for inaccurate grading from scanner defect detection is called over detection. Over detection is when the scanner identifies a feature in the board as a defect, but the feature is not truly a defect. These false positive defects may result in the scanner assigning a lower grade than the true grade because a larger cutting could have been placed over the false defect.

The last detection category for inaccurate grading of a board is partial detection. Often scanner sensors are able to identify the majority or parts of a defect but not the entire defect. This may or may not affect the board grade. The structure of NHLA lumber grading rules presents situations where being accurate within an 1/8th of an inch is essential, yet other situations where complete defect detection is not required to assign the correct grade. In these situations, the scanner partially identified the actual defect and assigned a higher lumber grade than the true grade.

Table 2 gives a summary of the detection errors by defect type and species. The following section will explain why detecting certain types of defects is important for establishing board grade, detection ease or difficulty, impact of miss-identifying a defect and potential remedy.

4.1. Wane

Wane is the most common defect in high-grade lumber because it occurs on the outside of the log, near the clearest wood (Fig. 1). Defined as bark or the absence of wood on the edges or surface of a board, it is limited in both length and width allowed in upper grades of lumber, Select and Better (NHLA, 2015). Wane is considered unsound and not allowed in any cuttings. Profile cameras and lasers are the most important sensors in detecting wane. The threshold set for wane detection was for the cameras to identify anything that was greater than 1/32 in. in from the edge of the board but in general approximated to 1/8 in. to avoid false alarms caused by irregular edges. The reason for this is that by setting a threshold closer to the edge too much noise is picked up resulting in over estimate of wane length. For example, some species like hickory may have a coarse or stringy type appearance on the edge of the board because of the nature of the wood fibers or the saw tooth making the cut did not have a sharp enough edge. The threshold for wane width measurement also took careful adjustment and calibration because a certain amount of the wane would be surfaced off the rough lumber. Wane detection using the profile cameras and line lasers was very accurate and there was no single specific species that had a problem with wane detection. Wane can be on either face of a board, and on either edge of a face. It can be continuous, or broken into many sections. In the whole sample of 9454 boards, wane was detected 9366 times. The average wane length was 18″ and average width 0.35″. No boards were mis-graded because of wane detection.

4.2. Knots: large pale, small pin, cluster

Knots are very diverse lumber defects, both between species and within (Figs. 2–4). They are the result of a branch forming in the tree and growing out from the main trunk. Due to wood cells oriented often perpendicular to the face of the board, the fibers are more likely to split when drying and have a different density compared to the normal wood surrounding (Denig et al., 2000). Often, knots will have a darker color or be surrounded in enclosed bark, resulting in a loose or unsound knot

Table 1
Sensors used to identify different board features.

Feature	Color cameras	B&W cameras	Profile cameras	Line laser	Grid laser	X-ray machine	Main problem species
Board size		X	X	X			None
Wane	X	X	X	X			Hickory, R. Oak
Knots	X	X	X	X	X	X	Ash, H. Maple S. Maple
Checks/splits		X	X	X			None
Worm holes		X	X	X		X	R. Oak, S. Maple
Rot	X	X	X			X	Ash,
Shake		X	X	X			Hickory, R. Oak
Iron stain	X	X		X	X	X	R. Oak, W. Oak
Pith		X		X			Ash, Cherry, S. Maple
Bark pockets	X	X		X	X	X	Ash
Surface roughness	X	X	X	X	X		Basswood, R. Oak, W. Oak

Table 2
Causes and frequency of inaccurate board grading discrepancies by species.

Species	Iron stain	Large knot	False knot	Black knots 1/4″ or less	Surface roughness	Worm holes	Shake	Rot	Pith	False mineral	Glass worm	Knot cluster 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

The scanner incorrectly graded an individual board for one or more of these reasons.

Fig. 1. Wane on white oak board.

Fig. 2. Large pale knot in ash board.

Fig. 3. Pin knots in red oak board.

Fig. 4. Knot cluster in cherry board.

(Hoadley, 1994). Knots are unacceptable for lumber grading purposes because during manufacturing they are susceptible to falling out, torn grain and will often split, creating an uneven break in finishing. In the whole sample of 9454 boards, sound knots (knots in which the surface is not broken) were detected 4890 times. The average sound knot diameter was 0.52″. Unsound knots (knots that break surface of the board due to a split, bark, hole, etc.) were detected 4873 times. The average unsound knot diameter was 1.25″. Holes that were typically a result of fallen out knot (due to knot disintegration during drying) were detected 4439 time, with average diameter of 0.84″.

Grain deviation identified by black and white camera watching line laser and dot lasers is the main information to identify knots, followed by color camera to identify the contrast between knotty area and normal wood fiber structure. X-ray is used to eliminate false positive errors in cases where discolored area such as a boot print may be first identified, but then eliminated if there is no accompanying change in underlying wood density.

Large pale knots are the knots that have the same color as the surrounding clear wood. These knots are difficult for the color cameras to detect because of the lack of color difference between the knot and surrounding clear wood. Large knots are particularly challenging defects to detect also because as the branch gets bigger, its density and grain deviation surrounding the knot are homogenized and increasingly appear like normal clear wood. Lasers and scatter cameras could identify the crack in the middle that forms across a knot after it is dried, and cuttings were not placed over a large split. It can also be challenging for human graders to decide how far into the pale knot a cutting can be placed, if at all. Out of the 725 boards that were incorrectly graded in the study, 110 were a result of under or partial detection of large pale knots.

Another type of knot that was a challenge for the scanners detection capabilities was classified as a pin knot, or small black knots, less than ¼-inch diameter. Ash and basswood were a particularly challenging species because of the lack of density changes in the knots. The color cameras were able to detect a change in color for these knots, but due to the small size, there often was not enough change in density for the x-ray machine to confirm the presence of the knot. Without defect confirmation from the x-ray, these small knots were dismissed as either a smudge of dirt, grease or another visual surface blemish but not a defect. As a result, a cutting would be placed on top of these small black knots and a higher grade would be assigned than what should have. It should be noted that many of these under detected knots were pin knots less than 1/8th inch diameter and are challenging for a human grader to find at production speeds. Inaccurate under detection of small black knots resulted in 96 boards being assigned a higher grade and higher value.

The last category for knots that were incorrectly identified would be knot clusters. The detection of knot clusters was excellent. Only four boards out of the 725 were graded incorrectly because of improper knot cluster under detection. Cherry as a species is notorious for knot clusters, formed by many small epicormic branches on the log surface. The NHLA grading rules do allow for any small knots less than 1/8th inch in diameter to be allowed in clear cuttings for cherry lumber, as well as any gum streaks or spots (NHLA, 2015). There were three instances where cherry boards were incorrectly graded because of under detection on knot clusters. For example, in cherry, being able to distinguish a clump of gum spots from a knot cluster was the give and take balance between detecting too much and not enough.

The only other board that was incorrectly graded because of the knot cluster detection was a yellow poplar board. In yellow poplar, knot clusters with a black center are unacceptable but dark green knot centers are acceptable in cuttings. This very fine line made knot clusters a particularly challenging defect to calibrate. In addition to limited color camera detection, lasers were able to determine grain deviation around some knot cluster s, but without a drastic difference in density and color, some knot clusters missed were a result of under detection.

The only other board that was incorrectly graded because of the knot cluster detection was a yellow poplar board. In yellow poplar, knot clusters with a black center are unacceptable but dark green knot centers are acceptable in cuttings. This very fine line made knot clusters a particularly challenging defect to calibrate. In addition to limited color camera detection, lasers were able to determine grain deviation around some knot clusters, but without a drastic difference in density and color, some missed knot clusters were a result of under detection.

The largest error for over detection of defects was in the category of false knots. There were 106 boards out of the entire study sample of 9454 boards that were graded in-correctly because of a false positive knot detection. The main causes for this over detection are burls, which would be a swirling of the grain near where a knot would form (NHLA, 2015). The scanner would identify these burls as knots because of the irregular grain pattern and fiber deviation being identified by the laser systems and the increased density detected by the x-ray, because commonly there was a knot just below the surface (Fig. 5).

4.3. Checks and splits

Seasoning checks are a defect formed when rapidly drying lumber

Fig. 5. Burl detected as a knot in red oak board.

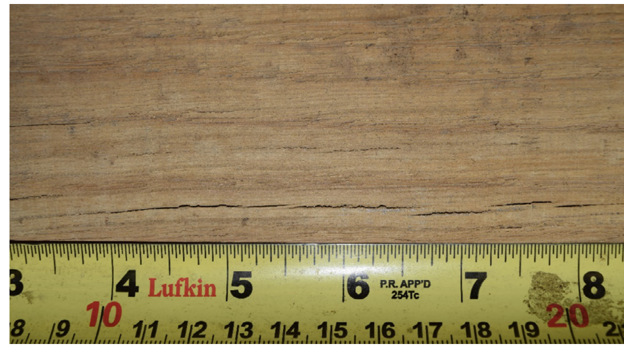

Fig. 6. Surface checks in white oak board.

(Fig. 6). Wood cells shrink during drying and as result of this loss of moisture, small cracks appear (Denig et al., 2000, Wengert, 1990). These checks can be on either the surface or end of a board. For grading purposes, normal season checks that can be surfaced out of lumber at standard surface thickness are acceptable in clear cuttings (NHLA, 2015). The detection of surface checks splits and cracks was extremely accurate. Any separation within 1/64th of an inch could be detected, but this level of detail did generate some false positives particularly when a board had an extremely rough surface or fuzzy grain appearance. In species such as red oak and yellow poplar, the level of precision on the scanner was adjusted to only identify separations of greater than 1/32nd of an inch to limit those false positives.

Splits are detected the same way as these ordinary season checks with the laser triangulation. Both the vertical and profile cameras are responsible for seeing how the laser reflects. Large splits, separation of wood that goes all the way through a board starting from an end, especially need the profile camera for accurate detection because the laser will not reflect as there is no material to reflect upon (Fig. 7). The scanner handled split and check detection exceptionally well, to the point where surface roughness of boards, where the normal rough grain surface was mistaken for a check or split resulted in 68 boards being graded incorrectly as a result. In the whole sample of 9454 boards, the splits and checks were detected 18,987 times. The average length was 1.95″ and average width was 0.15″.

4.4. Shake

Shake is a separation along the grain of a board between the annual growth rings and is considered an unsound defect (Fig. 8) (NHLA, 2015). Bacterial infection in the wood that weakens the early wood is most often the cause of ring shake, but wind throw from large storms can also result in the separation of the growth rings. Drying lumber does not cause shake, but can exacerbate its presence (Denig et al.,

Fig. 7. Split in white oak board.

Fig. 8. Shake in red oak board.

Fig. 10. Rot in red oak board.

2000, Wengert, 1990). Certain species are more prone to ring shake. Hickory and red oak were most common occurrence of shake in the study sample.

Detection of ring shake is mainly done with the lasers and both profile and black and white cameras. Similar to detection of a surface check, the scanner is accurate at picking up shake when there is a crack on the surface of the board. The majority of the incorrectly graded boards with shake detection as a reason had only partial detection and placed a cutting on top of the portion of the board with the shake not breaking through the board surface. Another reason for incorrectly identifying shake was that the grain separation was not perpendicular to the face of the board but rather at a bigger angle following the growth ring. Instances when the shake did not result in a 1/16th inch or larger separation on the board surface, detection was significantly hindered if the split was angled because it was too sharp an angle for the profile cameras to "see inside". Out of the 725 boards graded incorrectly, 30 were the result of under detection of shake.

4.5. Pith

Pith is the soft core at the center of a log (Fig. 9) (Hoadley, 1994) and is regarded as an unsound defect in the NHLA grading rules (NHLA, 2015). It is subject to extreme shrinking problems due to the proximity of juvenile wood. For upper grades of lumber that come from the outside portion of a log it is seldom an issue, but can be, when sawing closer to the center of the log. Often times the pith is never sawn into boards because the log defect core in the center of the log is made into either a railroad tie or a pallet cant. Higher value species where the lower grade lumber is worth more money may have more pith because it is cost effective to saw all the way into the heart of the log.

Fig. 9. Pith in soft maple board.

The scanner could accurately detect the pith when it broke the surface of the lumber, using both lasers and color cameras. Pith is also known as boxed heart if it is enclosed within all four board surfaces (NHLA, 2015). Boxed heart was often partially detected with the lasers and cameras able to pick up the surface of the board cracked from shrinkage. The grading errors that occurred due to pith or boxed heart detection were a result of cuttings placed over areas where the surface of the board was not cracked open and the pith was hidden. The x-ray was not able to pick up enough of a change in density from the less dense pith core. Ash, cherry and soft maple lumber species had the most occurrences of pith under detection. Partial or under detection of pith resulted in 29 boards being graded incorrectly.

4.6. Rot

Rot, or decay, is the fungal breakdown of wood cells (Fig. 10). There is a large spectrum of rot ranging from very advanced dry rot in which wood crumbles to the touch and white rot that is soft and spongy to incipient decay where the fungus is just starting to spread into sound wood cells (Hoadley, 1994, NHLA, 2015). Rot is difficult to detect for a scanner because of the minor color difference between the rot and normal clear wood. In rough lumber especially, incipient decay can closely resemble water stain. While lasers and color cameras struggle with detection of rot, while the x-ray can differentiate some changes in density if the rot is advanced. However, incipient decay that is starting to form, does not have enough density change to be detected consistently and as result cuttings were placed over rotten portions of the board. Ash was the most common species to have difficulty with rot under detection and this makes sense given the amount of standing dead trees starting to decay due to Emerald Ash Borer. The other feature of ash making incipient decay difficult to detect is that the decay looks very similar to the brown heartwood. In total 29 boards were graded incorrectly because of under or partial detection of rot, 24 of these boards were ash.

4.7. Worm holes

NHLA lumber grading rules describe any worm holes in lumber based on the average diameter of the hole itself. A pin worm hole is anything less than 1/16th inch in diameter, a spot worm hole is any hole between 1/16th inch to 1/8th inch in diameter and shot worm hole is a hole larger than 1/8th inch but smaller than ¼ inch. Any worm hole that is larger than ¼ inch in diameter is classified as grub hole. No worm holes are allowed in clear cuttings unless specified by the lumber order invoice as worm holes no defect (WHND). Pin, shot and spot worm holes are allowed in sound cuttings but grub holes are limited

Fig. 11. Worm hole in soft maple board.

(NHLA, 2015). Columbian timber beetle is one of many different insects that can bore into a tree during part of its life cycle and create these holes in soft maple lumber especially (Cassens, 2007).

Worm holes can create a challenge for detection, in being precise enough to identify very small details but also filter out false positives. If a worm hole diameter is less than one pixel size (0.19 mm or about 1/128″), there is a chance that it will be filtered out as a noise. Additionally, at higher speeds a worm hole can be missed because of sensor frame speed. From the nine species in this study, the two most common species to have boards graded incorrectly because of worm hole under detection were red oak and soft maple (Figs. 11–12). Unlike red oak, soft maple has gray or brown streak, also known as a flag, surrounding the worm holes. Because of this color feature, a special detection filter could be set where the detection sensitivity was increased and then any over detected worm holes not surrounded by a gray flag could be filtered out. Due to the drastic color indicator and this filtering technique, the worm hole detection in soft maple was considerably more accurate than in red oak. In the whole sample of 9454 boards, worm holes were detected 16,515 times. Out of the 725 boards that were graded incorrectly, worm hole under detection was responsible for 40 boards. The average diameter of a worm hole was 0.45 mm (0.018″).

4.8. Iron stain

Iron stain was the most common reason for a board to be graded incorrectly. Mainly in oak species of lumber, iron stain forms when the green lumber wet with moisture and tannic acid contacts ferrous metal (Wengert, 1990). Minor to moderate iron stain does not pose a major challenge to defect detection and can be filtered out. Heavily iron-stained boards (Fig. 13) pose a problem for two reasons. First, stain can obstruct cameras from detecting underlying defects (the same is true for human eye). Second, highly polished black patches that result from spinning conveyer rolls rubbing on a stationary board have such a dark shade of matte black stain and deposited ferrous metal on the surface, that they absorb, rather than reflect lasers that could detect grain deviation. This heavy iron stain will also confuse the x-ray, resulting in over detecting of defects. In these cases, detection algorithm was trained to delete any defects that overlapped with the iron stain. Iron stain is an intermittent issue that depends on season, anti-stain dipping of lumber and mechanical handling. For example, veneer mills use stainless steel rollers and other handling equipment to prevent iron stain. Iron stain is present in some regions and not often in others. In total, iron stain resulted in the largest number of boards being graded incorrectly, 198 out of 725. Red and white oak accounted for 125 of those incorrectly graded boards. It must be said that this is an equally difficult issue for a human grader.

Fig. 12. Shot worm holes in red oak board.

Fig. 13. Iron stain in white oak board.

4.9. Others: mineral streaks, etc

Other minor instances for grading errors included extreme mineral stain in yellow poplar boards that were a shade of black, much darker than the normal purple or olive streak (Fig. 14). Mineral streaks and spots can be limited in certain species such as oak and basswood based on the NHLA species specific rules. In the 13 instances of errors due to mineral streaks, most were extremely dark mineral in color that confused the laser systems and cameras so that a cutting would not be placed over the mineral at all. In the ash species, glass worm streaks that had included bark were confused with a bark pocket five times. The bark pocket detection on the scanner was very accurate in all species, including hickory, which has a lot of mineral, bird pecks, bark and other irregular features.

Fig. 14. Black mineral streak in yellow poplar board.

5. Discussion

The defect detection capabilities of the GradeView™ lumber grading computer algorithm and the Microtec Goldeneye 300 Multi-Sensor Quality Scanner™ are consistent with Buehlmann et al. (2007) findings that showed high quality scanners still struggle with complete detection of rot, shake and individual worm holes. For 92.2% of the board footage scanned by the automated grading system, the detection accuracy was good enough to assign the correct lumber grade. Complete detection of all defects is not always required to assign the correct board grade because the focus on the NHLA standard lumber grades is on the yield of clear wood, not the defects. If there is enough clear wood in the correct number of cuttings of a minimum size, perfect detection of small defects in marginal areas is not a requirement to assign the correct lumber grade.

Several defect detection issues should be addressed in future work. Severe iron stain accounted for the majority of the incorrectly graded boards, 198 out of 725. In certain areas of the hardwood lumber region, it is common practice to dip lumber in an anti-stain solution that eliminates the iron stain. While this might be feasible in sawmills that dip lumber year round, or for part of the year, sensor accuracy methods must continue to develop to resolve this issue for mills in regions that do not dip lumber.

The scanning detection accuracy of black walnut lumber should be addressed as well. Due to the dark color of walnut and how similar the knots are to clear wood, it is very difficult for scanning systems to detect consistently at the present time. This study did not include walnut lumber because of time constraints and a lack of satisfactory calibration. It should be noted that black walnut is not a high-volume species for majority of hardwood sawmills.

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 grades. This study did not use color sorting for grading maple, just standard grading rules. It is entirely feasible to identify heartwood and sapwood, but it was not done due to time and budget constraints.

Since the study scanner had been manufactured in 2014, sensors that are considerably more accurate have been developed and are installed in current scanners. Near-infrared lasers and more precise cameras make detection capabilities of pale knots much more accurate with hardwood lumber, especially when there is not as much of a density change for the x-ray machine to confirm the presence of the knot. The improved laser sensors will help with iron stain and shake detection as well, but further tests will be needed to confirm.

What we learned from this experiment is already being utilized to further develop scanner hardware and software. For example, the very accurate detection of cracks and splits is being further enhanced with special modules that improve the resolution of the cameras. This will result in a much more accurate and sensitive crack recognition. Pith recognition will be now based completely on software, using the thickness map as the main source. The pith creates a bump on the surface of the board, which is typically long and narrow, and visible on the thickness map. This can be processed in the algorithm, resulting in a correct detection of the pith. Due to lack of time during the calibration and small amount of boards with this defect, this software module had not been developed previously.

The scanner used for the test was a lineal-feed scanner. Microtec has also developed a transverse-feed scanner dedicated to hardwood lumber grading that will be easier to integrate into existing production lines. The recognition of defects with either system is nearly the same. While transverse-feed system was not physically tested in this study, a computer simulation based on the board data collected during our test shows that the percentage of grade change due to the conveyer chain blind spots on the bottom face of the boards is only around 0.20%.

6. Conclusion

The entire automated hardwood grading study scanned and analyzed 9454 boards and this paper reviewed the reasons why 725 boards were graded incorrectly (Table 1). Gazo et al. (2018) demonstrated the accuracy of the automated grading system to be 92.2% on-grade accurate based on the total volume (board footage) of lumber scanned. Published accuracies for defect detection and grading by human lumber inspectors has ranged from 48% to 75% (Huber et al., 1985, Kline et al., 2003, Pham and Alcock, 1998). The on-value accuracy of the grading trial found that the scanner assigned total grade dollar value was 99.5% of the true value, well within industry standards (Gazo et al., 2018). While there still are ways to improve the detection capabilities with sensors for identifying defects, this level of accuracy is well within the NHLA Sales Code accuracies of at least 80% of the total board footage being the correct grade and within 4% of the true lumber value (NHLA, 2015). The accuracy of this automated hardwood grading system along with upgrade trim optimization abilities and cost savings in labor and production rates show that this technology is ready to be adopted by industry.

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 to this article can be found online at https://doi.org/10.1016/j.compag.2018.09.025.

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. Autom. Sci. Eng. 5 (4), 677–695.

Bond, B.H., Kline, D.E., Araman, P.A., 2002. Differentiating defects in red oak lumber by discriminant analysis using color, shape, and density. Wood Fiber Sci. 34 (4), 516–528.

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

Cassens, D. 2007. Hardwood Lumber and Veneer Series: Soft Maple. FNR-290-W. Purdue Extension. Retrieved from https://mdc.itap.purdue.edu/item.asp?Item_Number=FNR-290-W.

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

Cho, T.H., Conners, R.W., Araman, P.A., 1990a. A computer vision system for analyzing images of rough hardwood lumber. In: 10th International Conference on Pattern Recognition, 1990. Proceedings, June 1. IEEE, pp. 726–728. https://doi.org/10.1109/ICPR.1990.118204.

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: IEEE International Conference on Systems, Man and Cybernetics, 1990. Conference Proceedings, November. IEEE, pp. 345–350.

Conners, R.W., Mcmillin, C.W., Lin, K., Vasquez-Espinosa, R.E., 1983. Identifying and locating surface defects in wood: part of an automated lumber processing system. IEEE Trans. Pattern Anal. Mach. Intell. 6, 573–583.

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, 48–63. https://doi.org/10.1117/12.969258.

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

Del Re, Riccardo., 2018, January 24. [Telephone interview]. Instalment Engineer, Springer Microtec Inc.

Denig, J., Wengert, E.M., Simpson, W.T., 2000. Drying Hardwood Lumber. US Department of Agriculture, Forest Service, Forest Products Laboratory.

Gazo, R., Wells, L., Krs, V., Benes, B., 2018. Validation of Automated Lumber Grading

System. Computers and Electronics in Agriculture (2018), https://doi.org/10.1016/j.compag.2018.06.041.

Hoadley, R.B., 1994. Understanding Wood: A Craftsman's Guide to Wood Technology. Taunton Press, pp. 19–37.

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

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

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

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.

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

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

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

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

Wengert, E.M., 1990. Drying Oak Lumber. Department of Forestry. University of Wisconsin-Madison, Madison, WI.