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Thomas, Edward, "An artificial neural network for real-time hardwood lumber grading" (2017). *USDA Forest Service / UNL Faculty Publications*. 314.
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Computers and Electronics in Agriculture 132 (2017) 71–75

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Original papers

An artificial neural network for real-time hardwood lumber grading

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ARTICLE INFO

Article history:
Received 15 August 2016
Received in revised form 17 November 2016
Accepted 20 November 2016

Keywords:
Artificial neural networks
Hardwood lumber
Grading
Sawing optimization

ABSTRACT

Computerized grading of hardwood lumber according to NHLA rules would permit fast assessment of sawn lumber and the evaluation of potential edging and trimming operations to improve lumber value. More importantly, to enable optimization of the hardwood lumber sawing process, a fast means of evaluating the potential value of boards before they are sawn is necessary. As log and lumber scanning systems become prevalent and common, these needs become more pressing. From an automation perspective, the NHLA lumber grades are difficult to implement efficiently in a computer program. Exhaustive approaches that examine every potential cutting size and combination to determine the grade give accurate grading solutions, at the cost of computation time. Other approaches have examined heuristic methods that implement key parts of the grading rules, or used artificial neural network methods, both with the loss of accuracy. Here, a different approach to computerized grading is examined that takes a hybridized approach using projected yield from cut-up simulation and neural network methods. This new hybrid approach has the advantage of both accuracy and high-processing speed. Such an approach lends itself to log sawing optimization with respect to NHLA grades and market values when internal log defect information is known.

Published by Elsevier B.V.

1. Introduction

The quality and the market value of hardwood lumber is determined by the NHLA lumber grading rules (NHLA, 2104). In general, higher grade lumber, such as FAS, F1F, and Selects, has fewer defects and larger clear, defect free areas. Lower grade lumber, such as 1 Common, 2A Common, and 3A Common, has greater numbers of large defects and smaller clear areas. Overall, the hardwood lumber grading rules form a complex set of specifications that a board must meet to make a specific grade.

Computerized grading of hardwood lumber is not a new concept. The first work published regarding computerized grading on lumber was performed at the USDA Forest Products Laboratory in Madison, WI (Hallock and Galiger, 1971). Although this early program was accurate and fast, 10 boards per second, it was limited. The program could handle a maximum of 22 defects and graded the board as if all defects were on a single face. With the addition of the FAS One Face (F1F) and Selects lumber grades the rules became more complex, as they required grading each face separately.

Researchers at West Virginia University (WVU) sought to implement the full NHLA grading rules in a computer program. The ReGS (Realistic Grading System) program, a lumber grading training tool, (Klinkhachorn et al., 1994) exhaustively examined a board to determine the best clear cutting combination and lumber grade. UGRS (Moody et al., 1998) represented a more advanced approach to lumber grading training that also included remanufacturing to produce a higher lumber grade through edging, trimming, chopping, and ripping operations. Like ReGS, UGRS took an exhaustive approach to grading lumber with the full NHLA rule set. These programs graded lumber 100% accurate at the cost of execution speeds.

The complexity of the lumber grading rules and the number of cutting unit permutations that must be examined requires exhaustive approaches to lumber grading that demand significant computing time, like that of ReGS and UGRS. Thus, other approaches to lumber grading have been explored. Boden et al. (2005) developed a statistical approach to predicting the NHLA grade of lumber. Their main goal was the development of grading software that performed at faster speeds than programs that implemented the full rule set, like ReGS and UGRS. Boden et al.'s (2005) approach used three variables that described defect dispersion on the board surface and one variable summarizing defect size to develop a statistical model. The model achieved an overall accuracy of 73.4%, but graded boards 771 times faster than UGRS (Boden et al., 2005). However, the question remained whether or not mis-grading 26.4% of a lumber sample was acceptable.

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http://dx.doi.org/10.1016/j.compag.2016.11.018
0168-1699/Published by Elsevier B.V.

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Schmoldt (1995) proposed an artificial neural network (ANN) classifier approach to grading parts and lumber that would be suitable for real-time processing operations. The best performing neural network configuration achieved an accuracy of 61.5%. This network used standard back-propagation learning and consisted of 3 layers and 19 input nodes, 15 hidden layer nodes, and 5 output nodes. Both Schmoldt's (1995) and Boden et al.'s (2005) approaches grouped the upper grades: FAS, F1F, and Selects together and treated the common grades separately. Schmoldt's ANN approach also classified boards as below grade if they did not meet 3A Common specifications.

Training an ANN using back-propagation is a computationally intense process. With today's multi-core computer architectures this is less of a concern, it is now feasible to examine much larger ANN models that can accommodate many input variable combinations. Those combinations that lead to correct results (e.g., correct grade) are weighted heavier than those which don't. In this paper, the use of ANNs larger than those typically experimented with in the past is developed and tested for the grading of hardwood lumber. The goal of this ANN grading approach is to be able to accurately grade lumber within the log before sawing. Using laser scanning vision systems, the defects on the surface of a hardwood log can be detected (Thomas and Thomas, 2011) and the internal defect manifestations estimated (Thomas, 2016). Using this full defect information, log sawing can be optimized to return the highest NHLA grade and value of boards possible. However, to accomplish this, a fast and accurate computerized means of grading lumber is required.

2. Methods

Lumber from the kiln-dried hardwood lumber database (Gatchell et al., 1998) supplied boards for the development and testing data samples. The databank is composed of boards graded to FAS, F1F, Selects, 1 Common, 2A Common, and 3A Common NHLA grades. This database was repeatedly graded by different certified graders and all discrepancies between the graders adjudicated to the grading rules. This database also served as the "ground truth" for the development and testing of the ReGS (Klinkhachorn et al., 1994) and UGRS (Moody et al., 1998) hardwood lumber grading programs.

For this study, the entire database was utilized and a total of 4147 boards were selected for the development sample and 2137 boards for the testing sample. Boards were randomly selected from the entire database without replacement to create the development and testing samples. The numbers of boards by grade for the development and testing samples are listed in Table 1.

In earlier approaches to lumber grading software, the upper grades FAS, F1F, and Selects were combined into a single grade (Boden et al., 2005), or F1F and Selects were not considered (Schmoldt, 1995). An F1F board must meet the minimum size requirements for a FAS board: 6-in. by 8-feet, have one face that grades as FAS, and the back face meet 1 Common requirements. The Selects grade is virtually the same as F1F, except for the minimum board size required, 4-in. by 6-feet for Selects versus 6-in. by 8-feet for F1F. The Selects grade is more commonly traded in the Northern States and less often in the Southern and Appalachian regions (AHEC, 2008). In addition, rule 50 of NHLA grading rules state that Selects and 1 Common can be mixed and sold together (NHLA, 2014). Thus, for the purposes of this project, the 1 Common and Selects grades were combined for this study.

The Fast Artificial Neural Network (FANN) software was used to develop and test a variety of neural network configurations and topologies (Nissen, 2003). Standard reverse or back propagation training was used. A symmetric sigmoid activation function was used on the hidden nodes, while the standard sigmoid function was used for the output nodes. The best performing ANN has 19 input nodes, 2 hidden layers with 231 nodes each, and 5 output nodes. The ANN was allowed to train for a maximum of 8000 cycles (epochs) using the entire training set. The average training time for the neural network was approximately 1.25 h.

A special version of the ROMI rough mill simulator (Thomas et al., 2015) was developed to determine the yield potential and the sizes of clear cuttings that could be obtained from each board. This version of ROMI was heavily modified where many routines such as multiple part grade support and salvage processing (where additional rips and chops are required) were removed. These specific processing options are computational expensive and more importantly, primary processing for clear parts provides the best indicator of a board's quality. Thus, this modified version of ROMI is a method that quickly determines board yield. ROMI processes boards according to a cutting bill (e.g. a list of part sizes needed) and optimally fits the parts to the available clear, defect free areas. The larger the defect free areas, the larger the part sizes produced. To accommodate a variety of board qualities, the cutting bill consists of five widths (1.0, 1.5, 2.25, 2.75, and 3.5 in.), and eight lengths (10, 15, 18, 21, 27, 33, 39, and 53 in.). Numerous part sizes and numbers of parts were experimented with. In the end, this simple cutting order consisting of a full range of part widths and lengths proved to be good predictors of grade.

Table 2 lists the data associated with each specific input and output node. Perhaps the most critical inputs are 3 and 4, primary part yield and average part size, respectively, determined by the ROMI simulator. Additional inputs to the ANN consisted of the width and length of the board. Board dimensions are a simple discriminator for determining if a board is FAS or F1F. The remaining 15 inputs characterize the size and count of the different defect types. According to the NHLA grading rules (NHLA, 2014), depend-

Table 1
Board counts by grade for the development and testing samples.

Lumber grade	Development sample	Testing sample
FAS	876	432
F1F	455	245
1C/Selects	1513	815
2A Common	1071	499
3A Common	232	146
Total	4147	2137

Table 2
Data description of artificial neural network input and output nodes.

Node	Input node description	Output node description
1	Board width (in.)	FAS grade probability
2	Board length (in.)	F1F grade probability
3	Primary part yield	1C/Selects grade probability
4	Average part size	2A grade probability
5	Total defect count	3A grade probability
6	Sound knot defect count	
7	Total sound knot area	
8	Unsound knot defect count	
9	Total unsound knot area	
10	Decayed area defect count	
11	Total decayed/rotten area	
12	Hole defect count	
13	Total hole surface area	
14	Pith defect count	
15	Total pith surface area	
16	Split defect count	
17	Total split surface area	
18	Total length lower edge wane	
19	Total length upper edge wane	

ing on the lumber grade, certain defect types and sizes are not permitted.

The output of the ANN consists of a vector of numbers that indicate the likelihood the board is a specific grade. The higher the number, the greater the probability a board is a specific grade. The grade with the highest value indicates the neural network assigned grade for the board. Table 3 shows the output for a 5 board subsample. Here the highest value, indicating grade, is highlighted for each board. Thus, the NHLA grade results for these 5 boards would be interpreted as, FAS, 1 Common, 3A Common, FAS, and 1C/Selects, respectively (Table 3).

3. Results

3.1. Grading accuracy

The general accuracy of the ANN grader is summarized by grade in Table 4. The greatest accuracy, 84.7% correct, was observed with FAS. The lowest accuracy, 65.7% correct, was observed with the F1F grade. An overall accuracy of 80.2% was observed for all grades. Table 5 provides an analysis of grading errors and their severity. The color bands indicate the ANN assigned grade. The center column, *Correct*, indicates the number of boards that were correctly graded by the ANN for each grade. By following the color bands you can see how many boards were erroneously assigned to other grades. For example, the blue band contains the boards that were graded as FAS by the ANN. Examining the blue band it can be seen that 44 F1F and 16 1C/Selects boards were incorrectly graded as FAS. Similarly, examining the results for 1C/Selects, shown in the green band (Table 5), it can be seen that 679 boards were correctly graded. Table 5 also shows that the largest error with 1C/Selects was confusion with neighboring grades where 70 2A Common boards were graded as 1C/Selects.

Most errors made by the ANN are incorrectly grading a board by either one grade higher or one grade lower. The bottom of Table 5 lists the totals and percentages of boards graded correctly or by how many grades off the ANN assigned grade was, showing that 1714 boards or 80.2% of the testing sample was graded correctly. In addition, 168 boards were incorrectly graded 1 grade high and 195 boards were mis-graded one grade too low (Table 5). These mis-graded by one grade boards comprised 17.0% of the testing sample. Thus, 97.2% of the boards were either graded correctly or within 1 grade of the certified NHLA grade. Fifty boards, or 2.8% of the sample, were assigned 2 grades, above or below the certified grade. No boards graded more than two grades from the certified grade. If the FAS and F1F grades are merged, a common industry practice, then the accuracy within the combined uppers grade is 91.1%, with 617 graded correctly of 677 boards, and for all grades becomes 84.4% with 1804 correct of 2137 total boards.

Table 3
Sample neural network output vectors.

FAS	F1F	1C/Select	2A Common	3A Common	Below Grade
0.8794	0.0063	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.9087	0.0006	0.3037	0.0000
0.0000	0.0000	0.0001	0.0329	0.9999	0.0000
0.9972	0.0086	0.0004	0.0000	0.0000	0.0000
0.0007	0.0004	0.9997	0.0000	0.0000	0.0000

Table 4
ANN grading and error percentages by grade.

Grade	ANN correct board counts	Percent correct	ANN incorrect board counts	ANN assigned board counts	Certified grader board counts
FAS	366	84.72	60	426	432
F1F	161	65.71	67	228	245
1C/Selects	679	83.31	123	802	815
2A Common	403	80.76	146	549	499
3A Common	105	71.92	27	132	146
Total	1714	80.21	423	2137	2137

Table 5
Analysis of ANN grading errors by grade and degree of error.

	Graded low				Graded high		
	Grade off by:				Grade off by:		
Grade	-3	-2	-1	**Correct**	1	2	3
FAS[1]	0	20	46	366	0	0	0
F1F[2]	0	12	28	161	44	0	0
1C / Selects[3]	0	4	98	679	18	16	0
2A Common[4]	0	0	23	403	70	3	0
3A Common[5]	0	0	0	105	36	5	0
Total	0	36	195	1714	168	24	0
Percent	0.0%	1.7%	9.1%	80.2%	7.9%	1.1%	0.0%

1. Boards graded by the ANN as FAS are shown in blue cells.
2. Boards graded by the ANN as F1F are shown in orange cells.
3. Boards graded by the ANN as 1C / Selects are shown in green cells.
4. Boards graded by the ANN as 2A Common are shown in red cells.
5. Boards graded by the ANN as 3A Common are shown in gray cells.

Table 6
Certified grading versus ANN grading volumes and values.

Lumber grade	Certified graded			ANN graded			Board feet difference	Value difference	Percent value difference
	Board count	Total board feet	Total value	Board count	Total board feet	Total value			
FAS	432	3459.3	3149.00	426	3415.0	3109.29	44.3	39.71	1.26
F1F	245	1844.2	1661.37	228	1706.3	1536.74	137.9	124.63	7.50
1C Selects	815	4569.2	2513.30	802	4466.3	2456.60	102.9	56.7	2.26
2A Common	499	2826.9	1371.08	549	3157.6	1531.44	330.7	160.36	11.70
3A Common	146	702.3	302.14	132	656.7	282.55	45.6	19.59	6.48
Total	2137	13401.9	8996.89	2137	13401.9	8916.62	0.0	80.27	0.89

To understand the accuracy that the ANN grader needs, one must be familiar with the NHLA rules and specifications and Article X regarding the inspection of lumber (NHLA, 2014). The NHLA rule book (NHLA, 2014) states that if a lumber buyer's inspection shows that an order of lumber is more than 20% from the specifications of the order, and the buyer and seller cannot reconcile the differences, they may request inspection by a certified NHLA grader. If the certified grader finds that the lumber meets less than 80% of the specifications of the order, then the seller is liable for the difference. If the total value difference is less than 4% of the invoiced amount, then the buyer is obligated to accept the order and pay for the inspection.

The value of the lumber for the certified graded (exhaustively graded by UGRS) and ANN graded samples were calculated using values for kiln-dried red oak as reported in the Hardwood Market Report (HMR, 2015). Table 6 lists the number of boards, board footage, and value of boards assigned to the certified grades and neural network grades. For the testing sample as a whole, the different board assignments within the grades averaged out and a total value difference of $80.27 or 0.89% between the ANN and NHLA certified grading assessments for the 13401.9 bdft sample. Examining the value differences within each grade, the lowest percent difference, 1.26% occurred with FAS. The greatest difference, 11.70% (330.7 bdft), occurred with 2A Common. For 2A Common, 50 more boards were assigned to the grade by the ANN grader than the certified grader. For all other grades the difference (error) in board footage assigned by the grading methods ranged from 44.3 to 137.9 bdft.

Using R (R Development Core Team, 2006), paired t-tests ($\alpha = 0.05$) were performed to test for differences between the lumber values of the certified graded and neural network graded samples. Given there were no differences between 80.2% of the two methods results, it is not surprising that there was no significant statistical difference.

3.2. Processing time

To determine processing time for the ANN grading approach a series of timing studies were conducted using a standard consumer grade laptop. The laptop consisted of an Intel Core I3 processor operating at 2.13 GHz. It was determined that UGRS required on average 0.4 s to grade a board. The grading of a board using ANN requires two steps. First, a summarization step where the primary part yield and average part size as well as sizes of the defects are calculated, this required on average 0.0125 s per board. The second step, the assignment of a lumber grade, required 0.00047 s per board on average. Thus, the total time the ANN approach takes to grade a board is 0.01297 s, making the ANN lumber grading method approximately 24 times faster than UGRS. The ANN method can grade 77 boards a second on a consumer grade computer.

However, in practice the ANN method performance will be faster. The timing tests conducted here involved reading the board data from a file and writing the summarized data back to file. This file was then read by the ANN and the grade assigned. In practice, the defect data will already reside in memory as a product of the sawing process. This data will be summarized and directly passed to the ANN, avoiding the reading and writing of files, a time consuming process. The ultimate speed and accuracy of this approach might permit this software to function as a lumber grading system in automated lumber inspection systems, or as part of the optimization in automated edging and trimming systems.

4. Discussion and summary

The development of an ANN to perform hardwood lumber grading was driven mainly by necessity. Although the source code for the UGRS program was available, the code was developed for an interactive Microsoft Windows environment. It would have been a difficult task to incorporate the UGRS functionality into the log sawing simulator developed for Linux (Thomas, 2013). These reasons combined with the processing speed of UGRS demanded the development of a new approach.

Although slower than the statistical approach by Boden et al. (2005), the ANN method achieved higher overall accuracy 80.2 versus 73.4%. If the upper grades are combined as in the Boden et al. study, then performance advantage of the ANN method improves to 84.4%, a 11.0% advantage. When comparing with typical real-world lumber graders, computer-based approaches compare favorably. Recently, one assessment of lumber grade accuracy found that human graders were correct on approximately 50% of their grading decisions (Kline et al., 2003). However, most of the errors discovered in their research study were related to Grade 3B and below grade boards, which were not part of this study.

5. Future work

The availability of a fast, accurate grading system makes it possible to implement a NHLA lumber grade optimization system for the RAYSAW hardwood log sawing program (Thomas, 2013). In addition, it may be possible to improve the accuracy of ANN lumber grader using an expert system that looks for common grading mistakes. This would require a deeper analysis of the system's grading mistakes and development of a series of corrections. However, one would have to be careful not to increase the computational load significantly, otherwise the speed gained using the ANN approach would be lost.

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