PERFORMANCE OF COLOR CAMERA MACHINE VISION IN AUTOMATED FURNITURE ROUGH MILL SYSTEMS

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ABSTRACT

The objective of this study was to evaluate the performance of color camera machine vision for lumber processing in a furniture rough mill. The study used 134 red oak boards to compare the performance of automated gang-rip-first rough mill yield based on a prototype color camera lumber inspection system developed at Virginia Tech with both estimated optimum rough mill yield and actual measured rough mill yield. Automated yield was found to be 56.3 percent compared to 69.1 percent (optimum) and 65.6 percent (observed). The relatively low yield based on the color camera lumber scanning system was due to the fact that image processing algorithms were very sensitive and tended to identify and cut out defects that were not truly present. The natural variations in the color of clear wood of red oak suggests that other sensing techniques along with color sensing will be needed to accurately characterize those lumber features that are important in furniture rough mill processing.

Cutting lumber into dimension parts is typically performed in a rough mill, the initial stage of the manufacture of furniture. The yield of parts that can be obtained from lumber in the furniture rough mill is a very important part of running a profitable furniture plant. With recent increases in lumber prices, lower available grades of lumber, and increased competition, rough mill yields play an even more important role in maintaining profitability. Wengert and Lamb (18) estimated that a 1 percent increase in yield in a furniture rough mill can potentially reduce its manufacturing cost by 2 percent. For a medium-sized rough mill, the cost savings associated with a 1 to 2 percent yield increase can range from $150,000 to $300,000 annually.

Traditionally, visual inspection of lumber is used to locate lumber features that are critical in the rough mill manufacturing process. Proper identification and treatment of those features that reduce the value and quality of the final products is key to achieving the best yield in the rough mill operation. Such features are more commonly referred to as lumber "defects." With visual inspection of lumber in the rough mill, which is still almost exclusively accomplished by human operators, the maximum potential yield is reduced by human judgment errors. It is very difficult to accurately and consistently locate lumber defects by human inspection at production speeds. A study conducted by Huber et al. (11) found the accuracy with which human operators recognized and located defects to be 68 percent. This level of inaccurate identification suggests a substantial negative impact on rough mill yields and costs.

Progress has been made in developing new technologies to help automate rough mill systems. This progress is apparent in the development of laser-guided gang-ripping technologies and defect marking systems for automatic chop saws (1). These new technologies are making it much easier for human operators to concentrate on locating those features on lumber that are important to achieving maximum yield, while maintaining a desired level of part quality in the rough mill. However, state-of-the-art technologies still rely on manual lumber inspection, and hence, still incorporate sub-optimal information into "optimization" solutions.

For the last several years, new systems have been proposed to completely automate the rough mill using machine vision technologies. Substantial work has been done in developing machine vision systems for automatic lumber inspection (3,9,12,13). Machine vision systems have the potential to handle more complex decisions to best match various lumber surface characteristics to an array of

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different part quality specifications. Every single defect including type, position, and size can be taken into account. A study conducted by Conners et al. (8) found that using color in machine vision systems can help reveal surface defects on lumber. More recently, progress has been made in establishing an automatic color image interpretation and defect recognition system that can be used to automate the lumber inspection process in rough mill systems (9). Although different results have been reported on the accuracy of this defect recognition system (4,9), no thorough investigation has been performed to assess its performance in a more realistic furniture rough mill setting.

The purpose of this study was to evaluate the performance of color camera machine vision for lumber processing in a furniture rough mill. Since many proposed automatic lumber inspection systems would involve a substantial investment, it is worthwhile to establish procedures that can be used to investigate the relative performance of these systems. This investigation sets up a procedure with which the performance of different automatic lumber inspection systems can be assessed and compared. More specifically, this study compares the performance of a color camera machine vision system to both optimum and observed rough mill processing by accomplishing the following objectives:

1. Measure the observed rough mill yield from an actual furniture rough mill;

2. Estimate the optimum rough mill yield through computer simulation using actual lumber data, including location and type of all grading features;

3. Estimate the automated rough mill yield through computer simulation with data input from a color camera lumber inspection system and compare it to the observed and optimum yield.

Materials and methods

The experimental procedures in this study included the preparation of lumber specimens, data collection techniques used at the laboratory and at the mill, optimization procedures, and yield analysis. Data collection in the laboratory for both manual and automated lumber descriptions involved digitizing board features such as width, length, and the type, size, and location of defects. Manual lumber description and defect digitizing was done very carefully and is assumed to be highly accurate, thus these data represent complete and perfect defect information. Optimization procedures included using a lumber cut-up program, ROMI-RIP (15,16), to estimate the best yield for two different scenarios: 1) based on perfect defect information (manual lumber description); and 2) based on defect information generated from an experimental color camera machine vision system (automated lumber description). Finally, the yield analysis involves measuring the part yield obtained in an actual rough mill and comparing yield results.

Lumber sample

A sample of 134 kiln-dried, skip-planed, 414, red oak board specimens was used in the study. The lumber was obtained from a rough mill in southwest Virginia. Due to field-of-view limitations in the color camera scanning system, the sample was selected such that a maximum board width of 13 inches was not exceeded. The average moisture content of the lumber was found to be approximately 7 percent at the time of the experiment. Sample board lengths consisted of 70 boards and 64 boards that were 10 feet and 12 feet long, respectively. Sample board width, which ranged from 3.00 inches to 12.75 inches, averaged 5.50 inches. Board widths were recorded based on the National Hardwood Lumber Association (NHLA) grading rule specification at a point one-third the length of the piece from the narrow end (14). The distribution of NHLA board grade is shown in **Figure 1.** Sample boards were cleaned to eliminate dark soil and grease marks to ensure maximum accuracy during both manual and automatic lumber digitization.

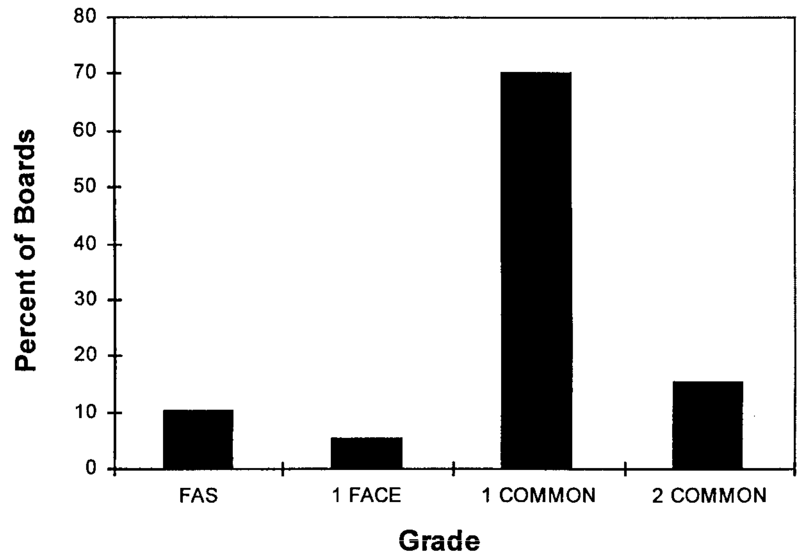

Figure 1. — The grade distribution of the lumber sample (based on the NHLA standard kiln-dry rule (14).

Manual board digitization

Board features were recorded manually using a technique for recording board defect data described by Anderson et al. (2). The information acquired from this digitization technique includes board size information and defect information. Lumber dimensions and defect areas were measured as rectangular shapes. One unit in both *x* and *y* directions in the Cartesian coordinate system corresponds to 1/4 inch. The *y* coordinate corresponds to the width of the board and the *x* coordinate corresponds to the length of the board. Defect sizes were recorded on both faces using the smallest bounding rectangle that enclosed the area of a defect. Defect types were recorded using an adoption of the code system employed by Gatchell et al. (10) in the red oak data bank. **Table 1** gives a complete listing of the defect types recorded and their codes.

In summary, the total data for each board included: a board label, coordinates defining the minimum bounding rectangle that encloses the board, coordinates defining each minimum bounding rectangle that encloses a defect, the board face on which the defect is located, and the defect type code. The format of the data files containing the board information was written in a data format consistent with ROMI-RIP'S lumber data input specification (15). More specific details on the digitization procedure are contained in other publications (2,19).

AUTOMATIC DEFECT DETECTION

The same 134 boards that were manually digitized were scanned by running them through a prototype machine vision system located at the Brooks Forest Products Center at Virginia Tech (12). The lumber scanning system is shown in **Figure 2.** The lumber was positioned on an infeed conveyor prior to scanning, such that the designated origin (0,0) of the scanned board image is the same as that of manual digitization. After the position of the board was established, it was released into the scanning system where a full-length color image was collected for the top face of the board. Based on a reference mark identifying the board face and the board end for the designated origin (0,0), the board is sent through the scanner as straight as the scanning system would allow. Although the infeed conveyor in front of the scanning system has a fence to keep the board straight, there was no fence within the scanning system to ensure straight movement through the system. The scanning process was repeated on the opposite board face. Every board was fed through twice because hardware was only available to scan one side per run.

Scanned color images for both faces were stored in the computer for further processing. For verification purposes, each board image was viewed on a computer display. Boards that were not scanned properly (e.g., improper light intensity or other obvious scanning errors) were re-scanned to ensure consistent results. An x-ray image also was recorded for each board with the scanning system but was not used in this study.

Color images for each board were later processed by the computer to automatically determine overall board length and width, the coordinates defining each defect size and location, the type of defect, and the number of defects per board. Algorithms used to process the color images were developed at Virginia Tech (5-7). Basically, these algorithms segment the color image to separate clear wood from potential defect regions. After segmentation, each of these potential defect regions is investigated further using a knowledge-based approach. This knowledge-based approach uses features from each of the defect regions, such as size, shape, location, and color, to verify if they are, in fact, defects and to identify the type of defect. The image-processing software used in this experiment classified defects into the following classes: wane, knot, split, hole, and void. These classes represent only a subset of the total number of defects that can be present on red oak lumber **(Table 1).** This automatically generated data was formatted to match the data format used in the manual digitization process.

As mentioned earlier, there was no fence available within the scanning system to ensure consistent alignment of the boards during scanning. For some scanned boards, substantial wander in the width-wise direction resulted in images that were not perfectly aligned with the manually digitized boards. An alignment software algorithm was developed to compare the shape of the scanned board to the shape of the true board as depicted through manual digitization. The algorithm adjusted board alignment by shifting data from the scanned images in they or width-wise direction. The effect of board alignment on yield in this study will be discussed in the Results section.

MILL STUDY

After all of the lumber was digitized, the same 134 boards were processed into furniture cuttings at a southwest Virginia rough mill. The mill was a rip-first rough mill system that used a laser-guided gang-ripsaw and a set of automatic cutoff (chop) saws. The process was controlled by a command center that optimized for a specified cutting bill.

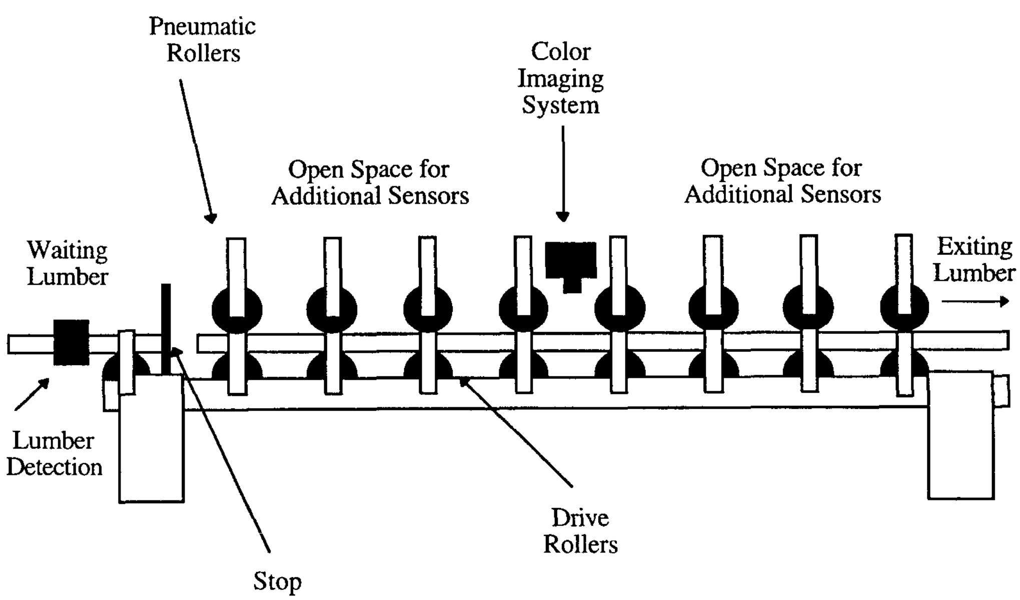

Figure 2.— Schematic of lumber-handling and scanning system with the color line-scan camera sensor used to scan the boards as they passed through the system.

Optimization employed two independent computer programs: 1) a program for maximizing strip yield at the gang-ripsaw: and 2) a program for optimizing part yield at the chop saws.

The ripsaw arbor system used by the mill was a fixed-blade-best-feed system. Under this system, all gang-ripsaw blades were fixed and boards were fed into a gang-ripsaw with a movable fence at the left edge of the incoming boards. The strips from the ripsaw were then moved to the chop saw station where mill operators examined strips for defects and then marked their location with fluorescent crayons. Next, marked strips were run through a mark sensing scanner to locate the position of defects and relay defect location information to the command center. The command center determines the optimum cutting of the strip based on defect location and cutting bill requirements and then directs the chop saw where to cut the strip. Finally, the system has the flexibility to remanufacture parts through either re-rip or re-chop salvage operations.

The mill's cutting bill during the study included 3 widths and 11 lengths. This cutting bill and the actual quantity of cuttings generated at the mill for the 134 board samples is listed in **Table 2.** The mill's command center achieves the quantity of parts by adjusting part priority values. For example, many 58.5-inch parts were required for the particular production run; therefore, all 58.5-inch parts were assigned a high priority to assure that enough parts were generated. On the other hand, very few 30-inch parts were required and they were assigned a relatively low priority. The part quality specified by the mill was Sound 2-Face furniture cuttings. Sound defects such as mineral streak, sapstain, and sound knots were designated to be acceptable defects and were allowed on either face. Also, the mill allowed small unsound defects (maximum size: l/4-in. diameter) for the production run.

Senior operators with the most experience were selected to make the key cutting decision at both the ripsaw and chop saw stations. Only one crosscutting line was used during the experiment to simplify the data collection activity. All parts generated at the mill were gathered and brought back to the Brooks Center Laboratory for further examination. In the laboratory, parts were inspected and grouped according to the original board, and the actual observed yield of every board was calculated. While inspecting all parts to ensure they followed the mill's part quality specification, a total of 143 parts (45 BF) were found to have unacceptable defects. All of these parts could be reprocessed with additional sawing to produce 143 acceptable salvage parts (31 BF). The size of these salvage parts was calculated such that yield was maximized according to the allowable cuttings shown in **Table 2.** The mill manager and saw operators were contacted to verify that these parts would, in fact, be further processed into salvage parts as determined in the laboratory. A complete description of the mill layout, material flow, data collection activity, and data preparation is contained in Widoyoko's thesis (19).

ROUGH MILL SIMULATION

Using ROMI-RIP (15,16), lumber data generated from both manual digitization and automated defect detection were processed using the same variables observed in the rough mill. Those variables consist of cutting bill, arbor type, blade spacing on the arbor, and allowable defects on the parts. The same arbor configuration used in the mill was simulated in ROMI-RIP. As mentioned earlier, the saw arbor type is fixed-blade-best-feed with nine spacings (in.) from left to right: 3.00, 3.00, 2.50, 1.75, 2.50, 2.50, 1.75, 1.75, 1.75.

The mill's cutting bill including quantity of obtained parts was set up for the ROMI-RIP simulations according to the actual cuttings generated in the mill **(Table 2).** To avoid the production of parts not specified in the cutting bill, desired part quantities were set slightly higher (5%) than the actual cuttings observed in the mill. Complex Dynamic Exponent, a part prioritization strategy that dynamically assigns each part size a priority based on its size and desired quantity, was the prioritization strategy option selected in the ROMI-RIP simulations (16).

To match the part quality criteria used in the actual mill, all acceptable defects were excluded from the list of board defects i.e., sapstains, mineral streaks, sound knots, and unsound defects with an area of 0.0625 in.^{2} or lower. DATAMOD (17), a data-modification program, was used to exclude these defects considered to be acceptable on the parts.

TABLE 1. — Defect types and codes used in identifying and digitizing board features.

Defect code	Defect description
2	Void (corresponding with crook and taper)
3	Pith
4	Decay
5	Shake
6	Pith-related tear or split
8	Wane
9	Sawline
10	Bark pocket
11	Grub hole (diameter 1/4 in. and over)
111	Shot worm hole (diameter between 1/1 6 and 1/4 in.)
211	Pin worm hole (diameter 1/1 6 in. or less)
12	Unsound knot
13	Burl with bark or check
14	Surface check
15	Sound knot
16	Machining defects
18	Incipient decay
19	Sticker stain
20	Bud trace with bark/check
22	Sapstain
23	Bird peck
24	Split
25	Mineral streak

TABLE 2. — Rough mill cutting bill and part quantities generated during the mill study (Sound 2-face quality).

Width	Length	No. of parts
1.75	10	41
	16	99
	20.5	97
	30	5
	32.5	79
	50	22
	58.5	64
2.5	10	27
	16	102
	26.5	65
	30	1
	34.5	54
	55.5	21
	58.5	62
3.0	10	23
	16	104
	26.5	81
	30	4
	44.5	88

With lumber data scanned from the color camera scanning system, there were occasions when the scanning system failed to detect all critical defects

TABLE 3. — Summary of optimum, observed, and automated yields for the 134 boards.

Yield study method	Operation yields			Part yields		
	Ripsaw	Chop saw	Total	Primarv	Salvage	Total
	(%)					
Observed	81.1	80,9	65.6	62.2	3.4	65.6
Optimum	85.2	81.1	69.1	67.4	1.7	69.1
Automated	80.1	70.3	56.3	47.5	8.8	56.3

present on the lumber. In the absence of these defects, ROMI-RIP will generate cuttings that include unacceptable defects. An analysis routine was developed to adjust yields to take these cuttings into consideration. Basically, the routine overlays the rip lines and crosscut lines generated by ROMI-RIP'S output onto the manually digitized board data. If a valid cutting contains an unacceptable defect, the routine saves the cutting in standard ROMI-RIP lumber format with the defects that are present on the cutting. All of the defective cuttings generated were then re-run through ROMI-RIP using the same cutting parameters as discussed previously to estimate a salvage yield. To prevent ROMI-RIP from edging the salvage pieces again, the routine also adjusted the width of the cuttings to be slightly larger. Since ROMI-RIP attempts to produce cuttings with glue quality edges, the slight adjustment in width is equal to the width of two sawkerf lines, appropriately applied to each edge of the part. The standard ROMI-RIP output is used to determine the effect of undetected defects on part yield.

Simulation output included total yield, individual board yield, part distribution, and description of primary and salvage yield (15). The distribution of part sizes generated from each ROMI-RIP simulation was validated by checking it against the observed cutting bill **(Table 2).** Except where noted in the discussion, there was very close agreement between the number of simulated part sizes and the observed. To check that all cuttings generated were of the required part quality, all recorded board features and the cutting lines generated in the simulation were displayed on the Cartesian grid system using ROMI-RIP'S graphical display utility (15).

RESULTS AND DISCUSSION

For the 134 red oak lumber samples, **Table 3** summarizes the yields for each of the three yield study methods. The first study method is referred to as the "observed" rough mill yield and represents the actual yield measured during the mill study. The second study method is referred to as the "optimum" rough mill yield and represents the best yield that can be achieved from the set of lumber given the use of a parts prioritization schedule. Note that optimum rough mill yield is based on manual board description and simulated cut-up. Finally, the third method is referred to as the "automated" rough mill yield and represents the best yield that can be achieved given board defect information from a color camera lumber inspection system. When comparing the various study methods in the following discussion, yield differences refer to absolute percentage point differences rather than relative percentage differences (e.g., 5% more yield indicates that 65% yield was obtained rather than 60% yield).

ROUGH MILL YIELD

The total observed yield at the furniture rough mill studied was found to be 65.6 percent **(Table 3).** Total yield was measured based on the total area of parts generated from the total input board area (kiln-dried dimensions). This yield was found to be 3.5 percentage points less than optimum (69.1%). The automated yield based on the color vision system was found to have the lowest yield (56.3%), which was 12.8 percentage points less than optimum.

Part lengths and widths obtained in the optimum yield study were distributed very similarly to the parts obtained from the observed yield study. The only notable difference in the optimum yield distribution was a greater (150%) number of 10-inch lengths generated for 1.75-inch-wide parts. This difference was due to the simulated salvage operation, which generated more of these 10-inch parts than observed in an attempt to increase yield. The automated yield simulation could not match the number and distribution of cuttings observed at the mill. In particular, there was a deficiency of wider parts (width = 3.0 in.). The lower recovery of cuttings was attributed to a smaller amount of usable clear area on the scanned boards due to many falsely detected defects (called false positive errors). Further observations on the impact of these false defect detection errors will be discussed later.

Most of the potential loss in yield at the mill was observed to occur at the ripsaw where the gang-rip saw yield (81.1%) was found to be 4.1 percentage points less than optimum (85.2%). Ripsaw yield was measured based on the strip area generated from the total board area. The observed yield at the chop saws (80.9%) was very close to optimum (81.1%). The chop saw yield was calculated based on the area of parts generated from the total input strip area. For the automated yield study, both ripsaw (80.1%) and chop saw yields (70.3%) were found to be the lowest of the three study methods.

in the observed yield study, primary yield and salvage yield were found to be 62.2 percent and 3.4 percent, respectively. Primary yield is calculated based on the total area of parts generated after only one rip operation and one chop operation. Salvage yield is calculated based on the total area of parts requiring subsequent rip or chop operations beyond that required for primary parts. Salvage operations are typically employed to increase part yield usually at an added rough mill manufacturing cost. Note that the least amount of salvage parts were generated through optimum yield (1 .7%) and the most through automated yield (8.8%).

EFFECT OF LUMBER DEFECTS ON OBSERVED ROUGH MILL PROCESSING

Table 4 lists all lumber features observed on the 134 board samples, including those features that were considered acceptable to the mill. The surface area of these features was measured by summing the areas of all defect types found on both sides of the lumber. The total area of these features was found to be 13,608 in.^{2} or approximately 12.3 percent of the total board surface area. Recall that sound knots, sapstain, mineral streak, and other unsound defects with areas of 0.0625 in.^{2} or lower were deemed by the mill as acceptable defects. The total area of unacceptable features for this mill was 11,767 in.^{2} or about 10.7 percent of the total board area. By allowing certain sound and small unsound features in the cuttings, an additional 1.6 percent of the total surface area of the lumber could be used to produce cuttings.

Table 4 shows that void makes up the largest unacceptable surface area, followed by wane, unsound knots, splits, and bark pockets. Void defects are typically used to describe board crook and taper, and, hence it is not a true "defect" in the sense of a surface feature on lumber. However, the large area implies that many of the boards are not truly rectangular and can lead to operator judgment errors, particularly during the setting of laser lines during the gang-ripsaw process. Presence of large void and wane areas can be one possible reason contributing to lower observed yield at the gang-ripsaw (81.1%) compared to optimum (85.2%).

As mentioned earlier, 143 parts generated in the observed mill study were found to have objectionable defects on closer examination. These 143 parts contained 149 unacceptable defects and are listed in **Table 5.** Wane was the most frequent defect remaining on the parts that required salvage operation. In the observed mill system, wane was left on primary parts intentionally in some cases with the plan being to remove residual wane in subsequent machining operations. As shown in **Table 5,** the second major cause of rejected parts was insufficient part width. Board crook and taper, which are described as void, contribute to insufficient part width. In the rough mill, parts containing wane or having insufficient width size are typically re-ripped at a separate rip saw salvage operation. In some cases, this salvage operation is planned in an attempt to achieve greater yield.

The observed mill system does a very good job identifying critical defect types as evidenced by a high chop saw yield (80.9%) compared to optimum (81.l%). Operators missed some unsound knots and splits **(Table 5),** but given the frequency of occurrence of knots and splits, the relative miss rate is low **(Table 4).** Because holes, bark pockets, and decay occur with much less frequency **(Table 4),** these defects caused parts to be rejected infrequently **(Table 5).** In any event, such occasional misses were not observed to have a practical impact on yield. These missed defects did, however, tend to increase the volume of salvage parts produced.

EFFECT OF LUMBER SCANNING ACCURACY ON AUTOMATED ROUGH MILL PROCESSING

The automated rough mill processing system was examined further by determining how defect detection errors in the color camera scanning system impacted yield. Defect detection accuracy was measured in terms of false negative error and false positive error. False negative error means defect areas on the board that the scanning system classified as clear wood. False positive error means actual clear wood areas that the scanning system classified as defect. Areas relating to both false negative error and false positive error are measured by comparing the lumber features generated by automatic scanning with those of manual digitization. False negative and false positive errors were found to be 1,397 and 12,909 in.^{2}, respectively. False negative error and false positive error corresponds to 1.3 and 11.7 percent, respectively, of the total lumber surface area (110,334 in.^{2}).

To assess the effect of false negative and false positive errors on the scanned yield, the scanned data file was systematically adjusted to include defects that were truly present and to remove those defects that were truly clear wood. Since the area associated with false positive error was quite large (11.7% of the board surface area), this error was expected to have a large effect on yield. By removing all false positive areas from the scanned board data files and re-running ROMI-RIP, the effect of false positive error on yield was estimated. The scanned yield with false positive areas removed is found to be 68.7 percent, which is very close to the optimum yield (69.1%). This yield is 12.4 points higher than the original scanned yield of 56.3 percent. Others have noted that the color scanning system is very sensitive when scanning red oak lumber and it tends to identify defects that are not truly present (4,9,). However, it has not been known until now how large an impact this sensitivity can have on part yield.

The scanning sensitivity and resulting false positive error can be attributed to the presence of acceptable lumber features that tend to be darker than clear wood. Examples of such features include mineral streak, sapstains, sound knots, dirt, or unusual textures/grain patterns on the lumber. As stated earlier, the present color camera machine vision system is limited in the recognition of the following five feature types: wane, knots, holes, splits, and void. When the system confuses an acceptable feature such as mineral streak for an unacceptable defect such as a knot, a false positive error will occur.

Since mineral streak, stains, and sound knots are likely features that could generate false positive errors, their effect on potential yield was investigated. This effect was investigated by including mineral streak, sapstain, sound knots, and others as unacceptable defects in the manually digitized board data files. When mineral streak, sapstains, sound knots, and all small unsound features are treated as defects, optimum ROMI-RIP yields dropped by 5.1 percentage points. Therefore, it can be concluded that false positive errors due to a limited feature vocabulary can have a substantial effect on yield. Recall that false positive error caused a yield reduction of 12.4 percent-

TABLE 4. — Defect areas manually observed on the 134 board specimens. The total usable board surface area is 110,334 in.^{2}

Defect types	Area
	(in.^{2})
Void	7,592
Wane	1,909
Unsound knot	1,223
Sapstain	963
Mineral streak	794
Split	442
Bark pocket	354
Machining defects	I 05
Hole	82
Sound knot	75
Sawline	22
Decay	19
Bud trace	12
Surface check	9
Shake	7
Total area	13,608

TABLE 5. — Frequency of defects left on rejected parts needing rework in observed rough mill yield study.

Type of defect	Frequency
Wane	57
Insufficient width	42
Unsound knot	26
Split	17
Hole	4
Bark pocket	2
Decay	1

age points. Since 5.1 percentage points of this reduction are explained by the limited feature vocabulary, other natural variations in the color of clear wood exist that have an equal, or perhaps greater, effect on the sensitivity of the defect recognition algorithms.

Since the area associated with false negative error is small (1.3% of the board surface area), this error was expected to have a small effect on yield. To confirm this, all errors were corrected (false positive areas removed and false negative areas added) from the scanned board data files and then ROMI-RIP was re-run on the modified board data. The yield with all errors corrected was found to be 67.8 percent (an increase of 11.5 percentage points over the original automated rough mill yield, 56.3%). Compared to the yield with only false positive error areas removed (68 .7%), the net effect on yield is a 0.9 percent reduction. The relatively small net change in yield confirms that false negative error has only a small impact on yield. However, in terms of parts rework for salvage, false negative errors lead to almost double the volume of parts that have to be reworked (90.9 BF vs. 45.6 BF). Also, the greater amount of salvage volume produced resulted in a greater number of smaller parts that are not needed in the cutting bill.

Effect of board alignment on automated yields

As mentioned earlier, the effect of a board not running straight through the system can have a substantial effect on yield. Most of the scanned boards ran relatively straight through the system. However, due to factors such as uneven lumber thickness and crook, approximately 10 percent of the boards deviated over 1/2-inch from true end-to-end alignment. To assess the potential effect of board alignment on yield, scanned lumber data were processed with ROMI-RIP both before and after images were aligned with the manually digitized data. The yield before and after alignment resulted in 49.0 percent and 56.3 percent, respectively, a difference of 7.3 percentage points. Therefore, misaligned lumber through a scanning system can have a substantial effect on yield.

Effect of defect representation on yield

Yield based on modified scanned board data files with all errors corrected (67.8%) was 1.3 percentage points less than optimum yield (69.1%). It would appear that these two yields should be the same because the modified scanned data should be identical to the manual data. This is not the case because when boards are manually digitized, the human digitizer makes certain judgments as to how many rectangles should be used to describe a certain defect area. The automatic defect recognition system tends to break a defect area down into a more complicated array of rectangles than is typically done manually. Therefore, the two sets of data are not exactly the same. The optimization algorithm in ROMI-RIP will proceed in a different manner on board files from these two sets of data. A yield difference of 1.3 percentage points between the two data sets is significant, and suggests that some future work will be needed to optimize the representation of defects in automatic lumber scanning systems.

Summary and conclusions

For several years, color camera machine vision systems have been proposed as a technology that can replace the manual lumber inspection process in the furniture rough mill. Although this belief has been the motivating force behind the development of new automated systems, no study has been available to justify how well color camera machine vision systems can compete with current state-of-the-art rough mill systems. Therefore, the purpose of this study was to rigorously evaluate the performance of color camera machine vision systems for lumber processing applications in the furniture rough mill.

The color camera machine vision system tested was developed at Virginia Tech. This system is able to scan full-sized lumber at industrial speeds and determine the size and shape of lumber along with the location and type of defects present within the lumber. The machine vision system was compared to an existing state-of-the-art rip-first rough mill facility that uses a laser-guided gang-ripsaw and a series of semi-automatic chop saws that can optimally chop strips into dimension parts based on operator-placed crayon marks indicating usable strip sections.

A sample of 134 red oak lumber specimens was used in this study. First, the lumber specimens were carefully hand-digitized for an accurate description of size, shape, and location of all lumber features present, such as knots, wane, stain, splits, and holes. Second, the lumber was scanned with the color camera machine vision system developed at Virginia Tech. This scanning resulted in a machine description of the same features obtained through manual digitization.

The lumber specimens were processed in an actual rough mill as Sound 2-face furniture parts of specified widths and lengths that were typically produced at the mill. Observed yields were recorded at the mill and later verified for consistency and accuracy in the laboratory. Both the manually digitized lumber data and the scanned lumber data were analyzed using ROMI-RIP, a rip-first rough mill simulation software package. Similar conditions as observed in the rough mill related to cutting bill specifications, arbor set-up, cutting priorities, and desired part quality were included in the ROMI-RIP analysis. The analysis resulted in two sets of yield information, one representing optimum yield (the best yield that can be attained for the given set of lumber) and the other representing the automated yield (the yield that would be attained for a proposed automated system using color camera machine vision). These two simulated yields were compared with each other and with observed yields from the mill study.

The following noteworthy results and conclusions arose from this study:

1. The total observed yield in the rough mill (65.6%) was 3.5 percentage points lower than the optimum yield.

2. The major portion of the rough mill's yield loss was observed at its ripping operation where observed ripsaw yield (81.1%) was found to be 4.1 percentage points lower than the optimum.

3. The observed chop saw yield (80.9%) is observed to be only 0.2 percentage points lower than the optimum yield.

4. Compared to the optimum, over twice as much volume of salvage parts was generated in the observed rough mill, which can lead to higher processing costs.

5. The yield from the scanning system is the lowest (56.3%) of the three yield study methods, 9.3 and 12.8 percentage points lower than observed and optimum yields, respectively.

6. When compared to optimum, losses in yield for the machine vision system are estimated to be reduced by approximately 11.5 percentage points due to errors in defect detection accuracy.

7. False positive defect detection errors (actual clear wood areas classified as defect) are the primary cause for yield reduction for the machine vision system. These errors are caused by acceptable lumber features that tend to be darker than clear wood (e.g., mineral streak, apstains, sound knots, dirt, or unusual textures/grain patterns).

8. False negative defect detection errors (actual defect areas classified as clear wood) have very little effect on yield but double the volume of salvage parts generated.

9. Other secondary factors associated with automated systems such as precision material handling and optimum lumber defect representation can also have a substantial effect on rough mill yield.

Although recent state-of-the-art rough mill systems are performing very well in terms of yield recovery, significant improvements can still be made through the development of automatic lumber inspection systems. Conclusions from this study indicate that automated lumber inspection systems based only on color camera scanning are not likely to perform at the level required by mill management for red oak lumber. Future research efforts are needed to improve the accuracy of lumber defect recognition systems by developing more sophisticated real-time image-processing algorithms and using a multiple-sensor approach for lumber inspection.

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