# EVALUATION OF COLOR-BASED MACHINE VISION FOR LUMBER PROCESSING IN FURNITURE ROUGH MILLS

by

Agus Widoyoko

Thesis submitted to the Faculty of the
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of
Master of Science
in
Wood Science and Forest Products

APPROVED:

D. Earl Kline, Chairperson

F.M. Lamb

J.K. Wiedenbeck

March, 1996

Blacksburg, Virginia

Key Words: Lumber, Yield, Defect Detection, Machine Vision

# Evaluation of Color-Based Machine Vision for Lumber Processing in Furniture Rough Mills

by

Agus Widoyoko

D. Earl Kline, Chairperson

Wood Science and Forest Products

## (ABSTRACT)

This research study examined the potential application of a color-based machine vision system under development at Virginia Tech for lumber processing in the furniture rough mill.

The evaluation was done by conducting a yield study using 134 red oak boards. ROMI-RIP, a rip-first simulation program by Thomas (1995), was used to simulate yields for both the manually digitized lumber data and the machine vision scanned lumber data. The color-based machine vision system was evaluated by comparing the optimum yield obtainable when using lumber data derived from the automatic scanning system to: (1) observed yield from an existing state-of-the-art rip-first rough mill and (2) the optimum yield from manually digitized lumber data. Overall, the color-based machine

vision system resulted in about 17 percent lower yield than was measured in the rough mill and 20 percent lower than the optimum, based on manually digitized lumber data.

An analysis of the yield percentage point difference between the machine vision-based yields and optimal yields indicates: (1) approximately 11.5 yield points were lost due to errors in defect detection accuracy, (2) 7.3 yield points were lost due to errors in the machine vision material handling system, and (3) 1.3 yield points were lost due to data digitization and truncation errors. Since material handling, data digitization, and truncation problems are solvable with current technologies, future research should focus on developing systems that can improve the accuracy of feature recognition in lumber.

## Acknowledgments

I would like to express my gratitude and deep appreciation to Dr. D. Earl Kline for his patient guidance and support in completing this thesis. He has provided encouragement and advice through out my Master's Degree Program at Virginia Tech.

I would also like to thank to Dr. F.M. Lamb and Dr. J.K. Wiedenbeck for kindly serving as member of my graduate committee and their support and valuable comments. Thank and sincere appreciation to Mr. Philip Araman on behalf of USDA Forest Service, Southern Experiment Station for providing wood samples and assistance. Again thank and great appreciation to Dr. J.K. Wiedenbeck on behalf of USDA Forest Service, Northeastern Forest Experiment Station for providing the digitizing equipment and valuable help.

Acknowledgment is also sent to Vaughn Bassett furniture company for providing place, equipment, and personnel during mill study. Thank and great appreciation to manager and all personnel involved in the study for valuable support and good cooperation.

I wish to thank also to Matt, Paul, Xiao, Oleg, Urs, Hartoyo, Hezli, and Dias for their help in pursuing this research. I also thank to all technicians at Brooks Forest Products Center for their cooperation during this research.

Special thanks to my wife, Widji Astuti; my daughter, Yunita Guswitasari; and my son , M. Arief Guswandi, for their love and sacrifice in Indonesia during my study in USA.

# Table of Contents

# List of Illustrations

# List of Tables

## Chapter 1

# 1.0 INTRODUCTION

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 (1994) estimated that by increasing part yields by 1 percent, mills can potentially reduce the rough mill manufacturing cost by 2 percent.

Traditionally, visual inspection of lumber is central to locating lumber defects that are critical in the manufacturing process. Proper inspection of lumber and the location of defects that affect the quality of the final products is key to achieving the best yield in the rough mill operation. In the present rough mill production environment, where visual inspection is accomplished by human operators, the maximum potential yield is typically reduced by human judgment errors. It is very difficult to inspect various defects on the board optimally and consistently by human inspection. A study conducted by Huber et al. (1985) indicated that the ability of human operators to recognize and locate defects was only 68 percent from perfect. Such findings indicate great potential for reduced costs and sound justification for developing systems which can automatically recognize and locate defects on hardwood lumber.

Progress has been made in developing new technologies to help automate rough mill systems. This progress is apparent in the development of new laser-guided gang-ripping technologies and defect marking systems for automatic chop saws (Klinkhachorn et al., 1989). 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 systems which are prone to making sub-optimal decisions.

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 (Kline et al., 1993). Machine vision systems have the potential to handle much more complex decisions to best match various lumber surface characteristics to an array of different part quality specifications. Every single defect including type, position, and size can be taken into account. A study conducted by Conners et al. (1985) 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 (Conners et al., 1992). Although different results have been reported on the accuracy of this defect recognition system (Conners et al., 1992; Araman and Wiedenbeck, 1995), no thorough investigation has been performed to assess its performance in a more realistic furniture mill setting.

The purpose of this study is to evaluate the performance of color-based machine vision for lumber processing in the furniture rough mill. Since many proposed automatic lumber inspection systems would involve 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 standard procedure from which the performance of different automatic lumber inspection systems can be assessed and establishes an industry benchmark with which the performance can be compared. More specifically, this research compares the performance of a color-based machine vision system to both a perfect lumber inspection system and an observed manual inspection system in an actual rough mill. Therefore, several important results are provided through this investigation including: 1) where and how much do color scanning systems need to improve to compete with present state-of-the-art rough mill systems, 2) potential for yield improvement in current state-of-the-art rough mill systems, 3) standard procedures for evaluating new rough mill inspection systems, and 4) standard procedures for collecting detailed data during rough mill yield studies.

**Chapter 2**

# 2.0 OBJECTIVES AND ASSUMPTIONS

## 2.1 Objectives

The objective of this study is to evaluate the performance of a prototype color-based machine vision system under development at Virginia Tech designed for scanning and processing dry surfaced lumber in the furniture rough mill. The general approach taken to address this objective involves comparing yields obtained from computer simulation with the actual yield of a rough mill.

In addressing the objective, the following specific tasks are established:

1. Determine the optimized yield through computer simulation with data input from manual board inspection.
2. Determine the optimized yield through computer simulation with data input from automatic visual inspection (color-based scanning).

3. Determine yields for the same cutting bill obtained in a mill study conducted at a gang-rip-first rough mill.

4. Evaluate the performance of the Virginia Tech machine vision system in recognizing surface features on the boards by comparing the results from tasks 1), 2), and 3).

## 2.2 Limitations and General Assumptions:

For the purpose of this study, it is necessary to recognize the following limitations and assumptions :

1. The study was limited to 4/4 red oak with the maximum width of 13 inches. This width limitation was imposed by the maximum width of boards that can go through the lumber scanning system.

2. The mill study was conducted at a rough mill with rip-first cut-up operations. Although this mill may not be representative of all furniture rough mills, it does include current (1996) state-of-the-art processing systems.

3. It was assumed that defect information from manual inspection provided an exact and complete description of all defects present in the lumber.

Chapter 3

# 3.0 LITERATURE REVIEW

This chapter reviews previous studies regarding the development of lumber processing in furniture industry. The chapter is divided into four sections: 1) furniture rough mill operations, 2) rough mill yield studies, 3) automated lumber processing systems, and 4) summary.

## 3.1 Furniture Rough Mill Operations

Cutting lumber into dimension parts is usually done in a rough mill, the initial stage of the manufacture of furniture. One primary objective in the furniture rough mill is to produce as many parts as possible from a given batch of lumber. Parts that are generated must meet a certain cutting bill which specifies the target part sizes (length and width). Furthermore, parts cannot contain more than a certain level of defects that are specified by management. Basically, there are two types of cutting systems in the rough mill operations: crosscut-first and rip-first. These two systems are distinguished by the sequence of cutting operations used to generate parts from lumber.

### *3.1.1 Crosscut-first Rough Mill*

Figure 1 illustrates a typical schematic layout of a crosscut-first rough mill operation. The typical crosscut-first rough mill starts with dry lumber from the dry kilns. The lumber is planed and then processed by cutting the lumber into desired lengths that are specified by the cutting bill. Then, the resulting pieces are sorted according to their length and are ripped into one or more parts of specified widths. The actual number of crosscut saws and rip saws and their layout depend upon the volume and type of furniture products manufactured.

### *3.1.2 Rip-first Rough Mill*

Figure 2 is an example of a rip-first layout used a furniture rough mill. A rip-first rough mill system starts by planing dry lumber. Lumber is then processed by gang-ripping lumber into one or more strips of specified widths. The process is continued by sorting the strips according to their width and then cutting strips into specified part lengths. In the layout described in Figure 2, strips are sorted for either fixed or random width and then sent to the appropriate chop saw line. Fixed width strips in this layout are processed through a moulder operation before cut to specified widths. The actual configuration and number of sawing operations in a rip-first rough mill depends on the volume and type of furniture products manufactured.

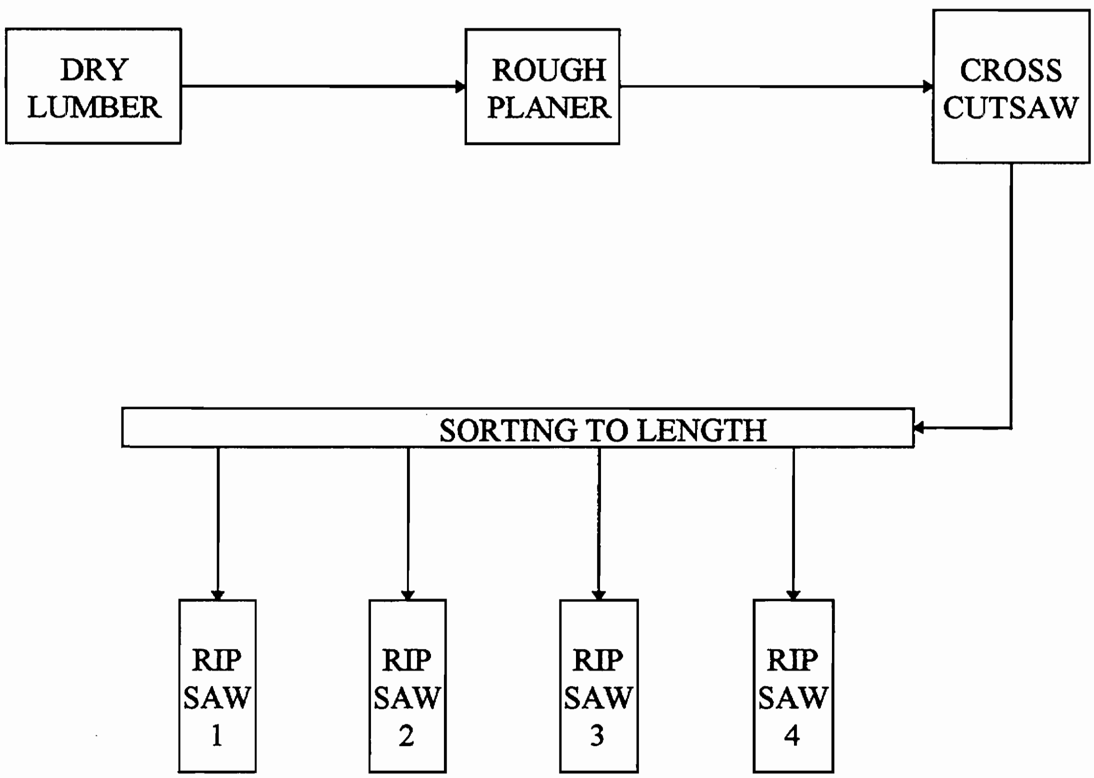



Figure 1. A schematic layout of a crosscut-first rough mill (Yun, 1989).

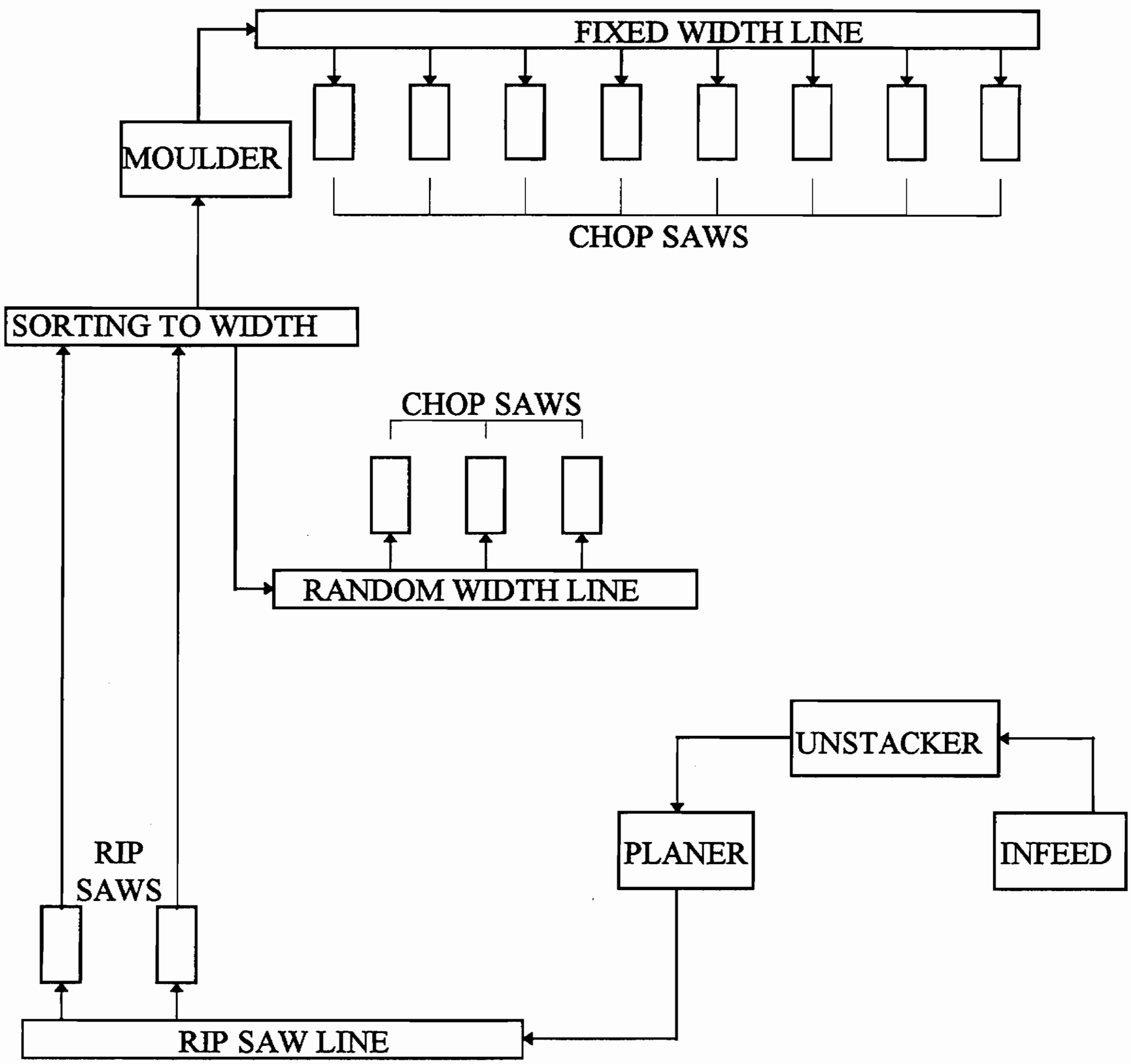



Figure 2. A schematic layout of rip-first rough mill operation (Wiedenbeck, 1992).

### *3.1.3 Crosscut-first vs. Rip-first System*

The choice of cutting sequence on rough mill operations has been addressed in several studies. A study by Lucas and Araman (1975) using computer simulation to investigate the effect of cutting sequence on yield and production cost found that cutting sequence affected the cost per part but did not significantly affect overall yields. Another study by Araman (1978) on four different manufacturing sequences showed similar yields between crosscut-first systems and rip-first systems. Hall et al. (1980) also studied the effect of cutting sequences on yields and production cost by processing No. 1 Common red oak lumber into six different parts lengths. Computer simulations were performed under a longest-length-first basis. They found that rip-first operations yielded 20 percent higher volume on longest parts (49 inches) whereas the crosscut-first operation yielded 23 percent higher volume on intermediate length parts (37 inches). There was no significant difference found on yields between crosscut-first operations and rip-first operations for the other part lengths considered (13, 26, 31, and 43 inches). Relating to production cost, they found that crosscut-first operations had higher labor cost but lower material cost than rip-first operations. Overall, Hall et al. (1980) concluded that there was no significant difference in the total production cost between crosscut-first and rip-first in their study.

### *3.1.4 Recent Trends*

Recent trends indicate that many new or updated rough mills are being designed with rip-first cutting operations. The main reason is that rip-first systems can produce higher yields on longer parts from lower grades of lumber (Gatchell, 1987b). Another reason is that rip-first systems require fewer, simpler operational decisions (Mullin, 1990). In addition, operators are able to recognize and locate defects easier on smaller width strips compared to full-width lumber.

Another trend in the rough mill includes greater automation of lumber processing operations. One reason for greater automation is to reduce labor costs (Huber et al., 1989). Another justification for automation is due to the increasing complexity of decisions that must be made to achieve optimum yield. With the development of new technologies for automatic lumber inspection along with rising costs in lumber and labor, the economic justification of automatic lumber processing systems is becoming easier (Conners et al., 1992).

## 3.2 Rough Mill Yield Studies

As stated earlier, with increasing lumber prices, rough mill yield is as a very important consideration for overall mill profitability. There are several factors affecting yield: lumber grade, drying, cutting bill, rough mill layout, operator skill, part quality, saw kerf, edging practices, lumber size, and grading rules (Wengert and Lamb, 1994).

Yield studies are very important for determining production efficiency in furniture rough mills. Studies can be done either in the mill or using computer simulation. Yield studies using computer simulation are preferred for several reasons: (1) computer based studies can trace part yield back to individual boards, (2) the computer can simulate different cutting bills, arbor settings, cutting sequences, cutting priority, etc. for the same lumber data set, and (3) computer-based studies are fast and repeatable. Although computer simulation is a good tool to gain a better understanding of rough mill yield, mill studies are also an essential part of understanding the true nature of rough mill yield.

### *3.2.1 Rough Mill Yield Simulation Models*

Rough mill yield studies using computer simulation were pioneered by Thomas (1962) when he developed a computer program to estimate yield from different lumber grades with various combinations of part sizes for a crosscut-first operation. The yield from this study were inflated by the fact that kerf losses were not taken into consideration. His concept, however, inspired other researchers to develop other computer programs to study rough mill yields.

Wodzinski and Hahn (1966) developed Thomas's concept into a crosscut-first computer program called YIELD. This program improved Thomas's program by identifying clear areas and kerf lines to be taken into account for extracting the longest possible parts. YIELD has been used in several yield studies to estimate part yield from specific species. Englerth and Schumann (1969) estimated part yields for 4/4 hard maple. Schumann (1971) estimated part yields for 4/4 black walnut. Later Schumann (1972) estimated part yields for 4/4 alder.

OPTYLD, a multiple rip-first computer program to maximize cutting yields, was developed by Giese and McDonald (1982) to maximize the total value of cuttings attained from a board. This program introduced a value-based optimization rather than solely a yield based optimization. This optimization strategy sacrifices a certain level of yield to obtain the highest value of cuttings.

CROMAX by Giese and Danielson (1983) is a further development of crosscut-first lumber cutup simulation programs. CROMAX developed an optimization algorithm based on the OPTYLD program by considering a large number of cutting combinations. The limitation of this program at the time of its development was the large amount of time required in computing a solution.

CORY developed by Brunner (Brunner et al., 1989) is a computer simulation program which can simulate either crosscut-first or rip-first operations. Compared to its ancestor, YIELD, CORY is much faster. The user can specify a dollar value in cutting bill to give prioritization to the parts. To assign a higher cutting priority for longer parts and minimize the number of short parts, CORY used the following formula:

$$\textbf{Priority} = \textbf{Length}^2 \cdot \textbf{Width}$$

The limitation of CORY's priority formula is that user can not set priorities for width. In further model development, Maristany et al.,(1990) used an exponential weighting factor in the priority formula:

$$\textbf{Priority} = \textbf{Length}^{WF} \cdot \textbf{Width}$$

With this formula the user can specify the priority of length in various weighting factors.

Lately, researchers have turned their attention to the development of computer programs involving optimization for rip-first systems. Stern and Bulgrin (1978) developed MULRIP which simulates multiple rip-first systems. Similar to MULRIP is RIPYLD by Stern and McDonald (1978). On the basis of MULRIP, Hoff et al. (1991a) developed a program called GR-1ST which tested the gang-rip options by adding a movable outer blade arbor. This program offers three different saw arbor options in the simulation: fixed saw arbor, variable saw arbor, and equally spaced saw arbor with a movable outer blade. The GR-1ST program does not simulate salvage operations in creating optimum solutions. Thomas et al. (1994) developed AGARIS by adding an algorithm to simulate salvage operations.

All those programs mentioned above have limitations in the type of arbors, the number of spacings on each arbor, and general flexibility of simulation. The latest simulation program for rip-first systems is ROMI-RIP (Thomas, 1995). This program was designed to overcome the limitations of its predecessor, AGARIS. The crucial difference from the previous program is its capability to process lumber based on desired part sizes and quantities. Using prioritization strategies, ROMI-RIP can dynamically adjust the value of part sizes in the cutting bill. ROMI-RIP can simulate gang-ripping-first operations with the following features (Thomas, 1995):

- *Part lengths: 30 primary, 12 salvage, or random*
- *Part widths: 10 primary, 8 salvage*
- *Salvage operations can use primary or salvage specific sizes*
- *15 spacings with a maximum arbor width of 48 inches*
- *6 arbor types: (1) fixed arbor, (2) fixed arbor with movable outer blade, (3) a fixed-blade-best-feed arbor, (4) best-spacing-sequence, (5) best-spacing-sequence with movable outer blade, and (6) an all-blades-movable arbor.*
- *Primary and salvage rip, crosscut, and strip counters*
- *Up to 200 lumber defects — allowable defects can be specified*
- *Cutting bill support for as many as 300 part sizes*
- *Dynamic or value-based cutting bill optimization*
- *Custom data file creation with or without random board selection.*

### *3.2.2 In-plant Yield Studies*

Very few studies have been conducted directly in the rough mill. One reason is the difficulty in gaining detailed information on yields of individual boards. Another reason is the limitation on variable manipulation in the process. Hall et al. (1980) conducted an in-plant study comparing the performance of rip-first systems to crosscut-first systems. Yun (1989) conducted an in-plant study to find out the potential improvement of a conventional rough mill with crosscut-first operation. Yun's study compared the observed level of yields in the mill to simulated yields. Wiedenbeck (1992) conducted mill studies at a crosscut-first furniture rough mill and a rip-first cabinet rough mill to find out the potential utilization of short length lumber in furniture and cabinet industries.

## 3.3 Automated Lumber Processing

Substantial efforts have been devoted to developing automated lumber processing systems for the furniture industry. Klinkhachorn et al. (1989) proposed an Automated Lumber Processing Systems (ALPS) where boards are scanned using video cameras to record all features present on the boards. The scanned images are processed by a computer program for tonal and textural qualities identifying board geometry, and defect type, location, and size. ALPS proposed to use a high-energy laser to cut lumber into furniture parts. The promising advantages of using laser cutting is its capability to cut non-rectangular with very thin kerf lines. The final part of ALPS is the automatic sorting of parts for size.

For automated defect detection, Conners et al., (1992) have developed a color line-scan-camera-based system which can recognize and locate defects on the boards. Algorithms developed in this study can differentiate boards from background, clear wood from potential defects, and types of defects. The study showed potential industry applications for the automatic defect detection system including automatic grading of hardwood lumber and rough mill automation.

Unlike in softwood mill operations, the degree of automatization in hardwood rough mills has progressed slowly. Presently, most rough mill operations are controlled by human operators. Huber et al.(1985) delineated possible human factors diminishing the yield of usable parts including skill, inattention, personal emotion, and exhaustion. As mentioned before, human operators were found to perform with 68 percent accuracy in lumber defect detection. Consistency was the main problem caused by human operators (Huber et al., 1985). This finding implies that a large potential gain can be realized in furniture rough mills through the use of automated cutup systems in lumber processing.

Before an automated lumber processing system can be developed, automatic lumber inspection systems that can accurately pinpoint lumber defects are needed.

Research and development of a machine vision technology for automatic lumber processing has been performed over the last several years to address this need.

### *3.3.1 Machine Vision Research*

In general, machine vision systems consist of an image scanning subsystem and an image interpretation subsystem. One or more sensing techniques can be applied in the system for image scanning. For example, black and white, color, x-ray, nuclear magnetic Resonance (NMR), and ultrasonic sensors can be used to scan information from a specimen (Szymani et al., 1982). In machine vision systems, an image interpretation subsystem that employs computer software is used to automatically extract meaningful features from the scanned image. The end result of a machine vision system is an automatic description of an object of interest (Conners et al. 1992).

Color-based machine vision pertains to a system that measures only the color saturation of a specimen to make inferences as to its quality or to locate features that affect its value. Since color is the primary sense used in human lumber inspection, the use of color in machine vision systems has been proposed to be sufficient for wood processing (Brunner et al., 1990 and Conners et al., 1992). Although color-based machine vision can not exactly duplicate human color vision, the use of color in machine vision has been explored extensively. Significant progress has been made by Conners et.

al. (1992) in developing algorithms for locating and identifying the features of hardwood lumber using color imagery.

Marszalec and Pietikainen (1993) used color analysis in automated visual inspection to classify clear areas based on degree of color homogeneity and recognize defects against clear wood based on spectral reflectance characteristics of defects. Misinterpretation may occur due to the limited capability of color analysis to differentiate the light intensity of every feature on the wood surfaces. Therefore only limited defects can be accurately differentiated by color imaging system such as knots, stain, color, and grain pattern (Kline et. al., 1993). Conners et al.(1992) determined that it was difficult to identify and locate all board features accurately using only color image data, thus multiple sensor machine vision systems that employ color, laser-based ranging, and x-ray scanning systems are being explored.

### *3.3.2 Virginia Tech Research*

Research at Virginia Tech has led to the development of a prototype machine vision system for hardwood lumber (Araman et al., 1992; Conners et al., 1992; and Kline et al., 1993). The goal of this work is to help U.S. hardwood sawmills and rough mills improve grading accuracy, product recovery, mill productivity, product conformity, and possibly improve marketing. The system consists of a material handling system, image collection system where scanners are located, a computer control system, and an image processing system (see Figure 3).

Kline et al., 1993 presented a complete review regarding a real-time image scanning system that has been assembled at the Brooks Forest Products Center at Virginia Tech. The system employs a multiple sensor defect detection system that consist of: 1) a precision lumber handling system, 2) a computer system, 3) a laser-based ranging system, 4) a color scanning system, 5) an x-ray scanning system.

The handling system works by moving lumber through a series of pinch rollers which are powered by a stepper motor. The handling system has a linear positioning accuracy of approximately 0.01 inches. The handling system can handle full size lumber up to 13 inches wide at speed up to 4 feet per second. The speed of the material handling system can be monitored and controlled by the computer.

Direct Memory Access (DMA) hardware is utilized to place board image data in the computer's main memory at the rate of 2 MB per second. With the DMA hardware, an image can be collected in real-time while the board is running through the system. The image, then, is stored on the computer's hard drive for further analysis and processing.

There are two Pulnix color line scan cameras and camera controllers employed by the color imaging system. Each line scan camera has 864 color sensitive pixels and can scan at a maximum rate of 2.5 Mhz. The surface of the board is illuminated using Tungsten-halogen incandescent light bulbs.

Two other scanning modalities are being developed in parallel with the color line-scan camera system described above. These scanning modalities include laser-based ranging and x-ray scanning. EG&G Reticon 128 x 128 high-speed array cameras are employed for the laser -based ranging system. As laser sources, 30 mW Helium Neon gas lasers at 632.8 nm wavelength are used to apply a laser light line onto the board surface. The range image generated by the array cameras is sent to the computer via the DMA board. An EG&G Astrophysics tungsten x-ray generator is used for the x-ray scanning system. The x-ray beam that passes through the board is collected using a Thomson linear detector to provide the x-ray image. The x-ray image is sent to the computer via the DMA. While laser-based ranging and x-ray scanning, will be important technologies for defect detection, they will not be addressed in this study.

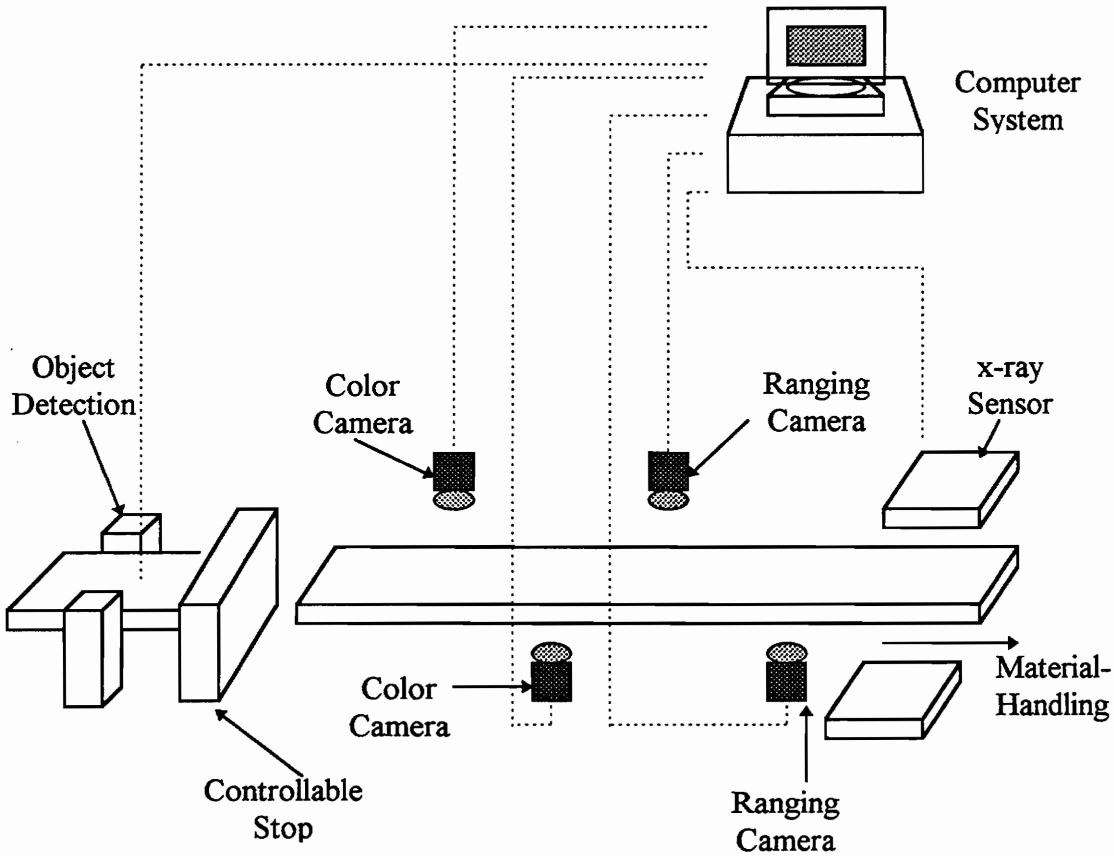



Figure 3. A view of the multiple sensor scanning system at VA Tech.

### 3.4 Summary

Increasing lumber costs and limited wood supplies indicate the need for the furniture industry to improve the efficiency of lumber utilization. Many studies have been done to develop systems that can increase production and reduce wood waste. Based on these studies, many furniture rough mill operations have recently adopted or are considering the adoption of state-of-art optimizing sawing systems to improve their production efficiency. However, these state-of-the-art systems still rely on manual lumber inspection and, hence, there is a potential for even greater yield improvement. Great progress has been made in developing scanning systems and computer programs for further maximizing processing efficiency. While great strides are being made in the development of machine vision systems for automatic lumber processing, little work has been performed to quantify how well these systems can compete in an actual rough mill environment. The focus of this research is to provide a comprehensive evaluation of machine vision systems for lumber processing in furniture rough mills.

## Chapter 4

# 4.0 MATERIALS AND METHODS

### 4.1 Research Overview

As stated earlier, the objective of this research will focus on the evaluation of a prototype color-based machine vision system for lumber processing. The color-based machine vision system employs color scanning to generate an image of the lumber and applies image processing and feature recognition algorithms (Conners et al. 1992) to automatically locate defects on hardwood lumber. This section develops the experimental procedures used to collect data and evaluate the results generated from this prototype machine vision system in a realistic furniture rough mill environment.

The experimental procedures in this study consist of the preparation of lumber specimens, data collection techniques used both at the laboratory and at the mill, optimization procedures, and yield analysis. Data collection in the laboratory for both manual and automated lumber descriptions involves recording the board features such as board width, board length, and type, size, and location of defects. Optimization procedures include using a lumber cut-up program to determine yield for two different scenarios: 1) based on complete defect information and 2) based on defect information generated from an experimental color-based machine vision system. Finally the yield analysis involves measuring the part yield obtained in an actual rough mill and comparing yield results.

### 4.2 Lumber Sample

A package of one-hundred-and-thirty-four 4/4 red oak, kiln dried, random width, 10-12 foot-long, NHLA graded, skip-planned boards is used in the study. The lumber is obtained from Cooper Wood Products, Inc., Rocky Mount, Virginia. As mentioned in the limitations, the sample is screened such that a maximum board width of 13 inches is not exceeded. The average moisture content of the lumber is determined to be approximately 7 percent during the experiment. 70 and 64 boards are 10 feet and 12 feet in length, respectively. The distribution of lumber widths is shown in Figure 4 and the distribution of grade is shown in Figure 5 respectively. The average width of the test specimens is 5.5 inch and 70 percent of lumber grade is 1 Common. The lumber is cleaned to eliminate dark soil and grease marks to ensure maximum accuracy during both manual and automatic lumber digitization

## 4.3 Manual Lumber Digitization

Board features are recorded manually using a technique for recording board defect data described by Anderson et al. (1992). The information acquired from this digitization technique includes board size information and defect information. Lumber dimensions are measured as a rectangular shape.

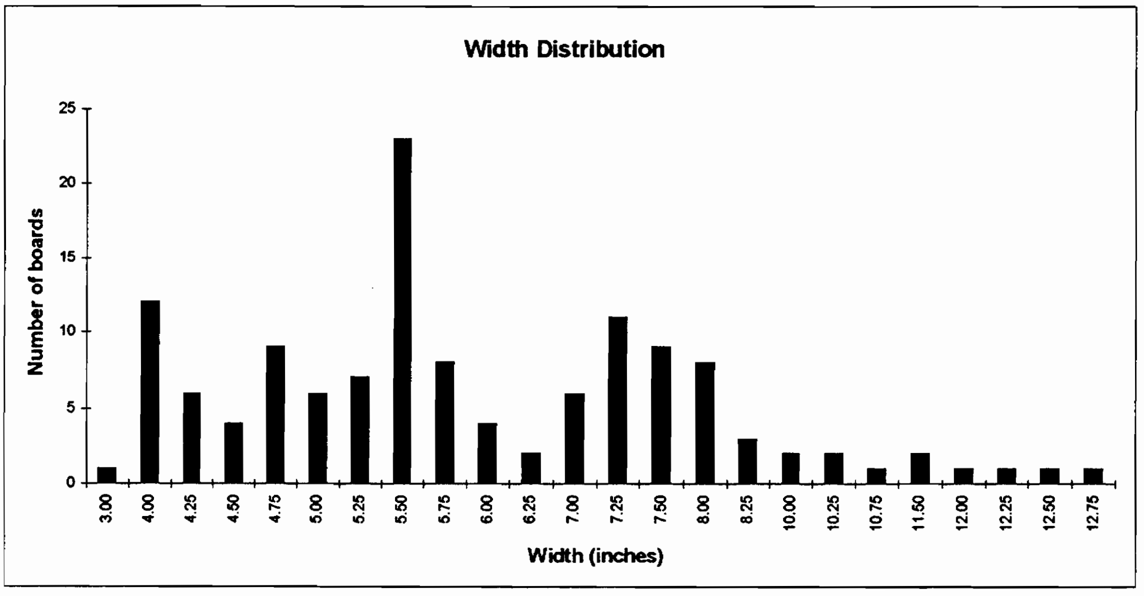



Figure 4. Width distribution of the lumber sample

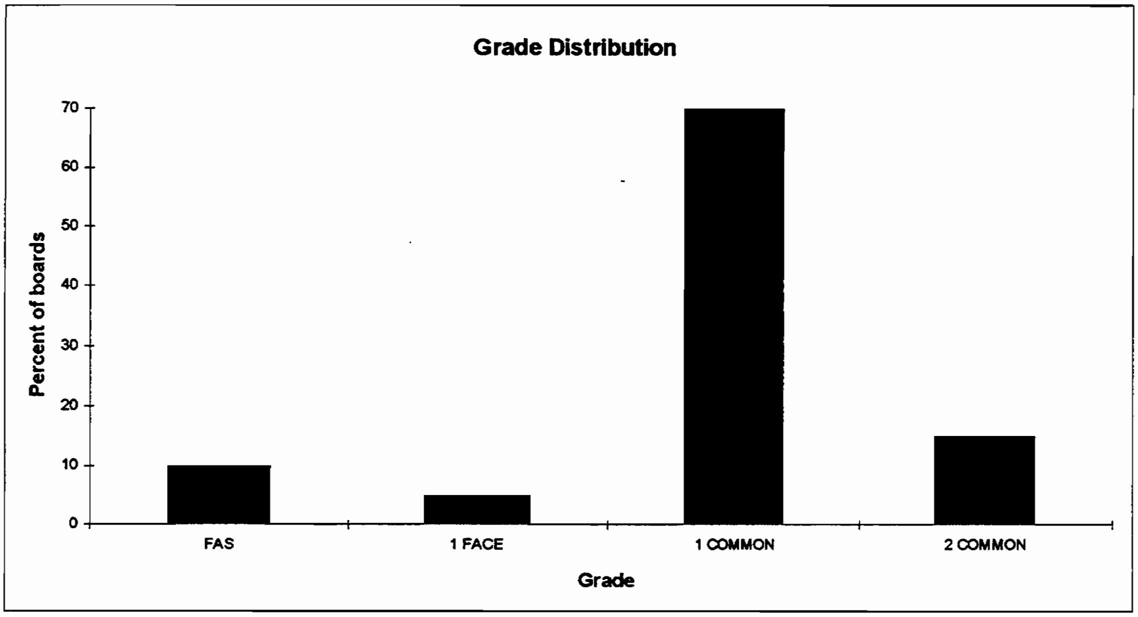



Figure 5. Lumber grade distribution (re-graded at the mill using standard kiln dry rule).

The Y coordinate corresponds to the width of board and the X coordinate corresponds to the length of board. One unit in both X and Y directions in the Cartesian coordinate system corresponds to 1/4 inch. The origin of the Cartesian grid is at the lower left corner of the board (0,0). The upper right coordinate represents the length, (l), and the width (w) of the board (l,w). The computer digitizer program records information about measured width and the bounding rectangle enclosing the board. For perfectly straight and rectangular boards, the bounding rectangle coincides exactly to the board edges. For crooked and tapered boards, however, the bounding rectangle's height is always larger than measured width (see Figures 6 and 7). Regardless the presence of crook or taper, the measured board width is recorded manually 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 (NHLA, 1990). Information on Figures 6 and 7 pictorially show the digitizing technique for recording board dimension (Anderson et al. 1992).

After information is recorded for overall board size, the next step in the digitization procedure is to record lumber defect information. Defect information consists of defect size, location, and type. Defect sizes are described using the smallest bounding rectangle that encloses the area of a defect. Hence, the size of defect is represented by a lower left corner coordinate ($Y_1$,$X_1$) and a upper right corner coordinate ($Y_2$,$X_2$) of the bounding rectangle for each defect.

The location of defects within a board are described relative to the origin (0,0) of the board. Figure 8 illustrates the technique of digitizing defects on a board. For example defect No.1 in Figure 8 is wane represented by a rectangle with its lower left corner located at coordinate 32,0 ($Y_1$,$X_1$) and upper left corner located at 37,7 ($Y_2$,$X_2$). The defect code for wane is 8 (see Table 1). In case of void, wane and other large defects, several rectangles are used to estimate the true shape of defect. For example, defect No.1 and defect No.2 in Figure 8 are used to describe the total segment of wane on a board.

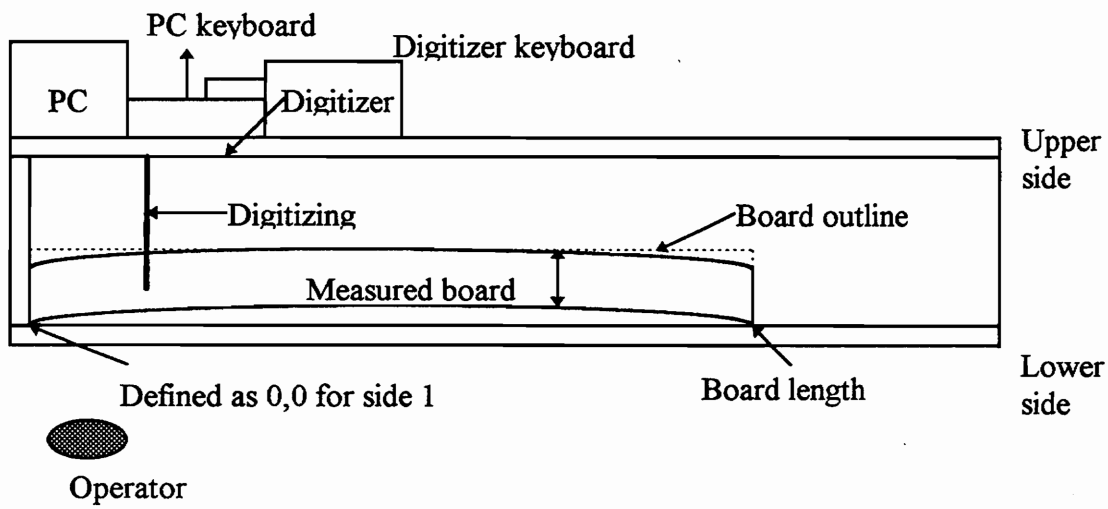



Figure 6. Top view of digitizing table for board face 1 (Anderson et al. 1992).

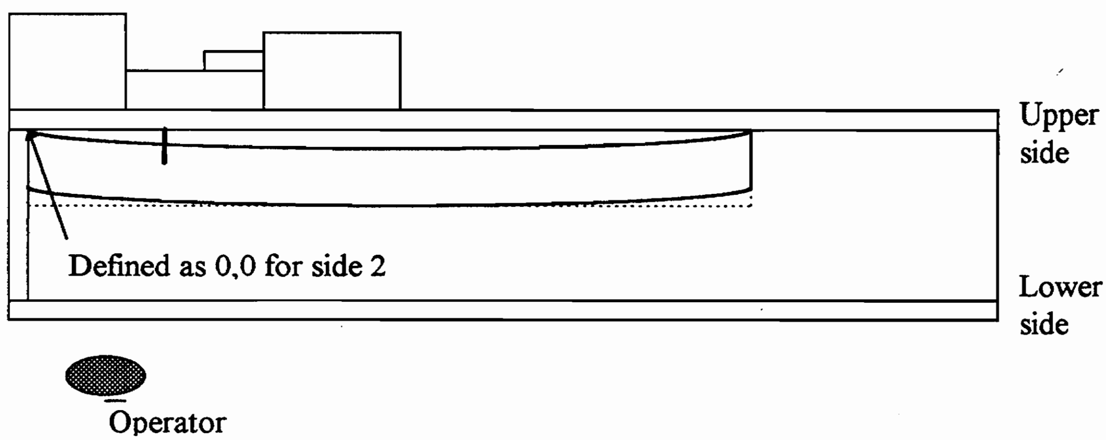
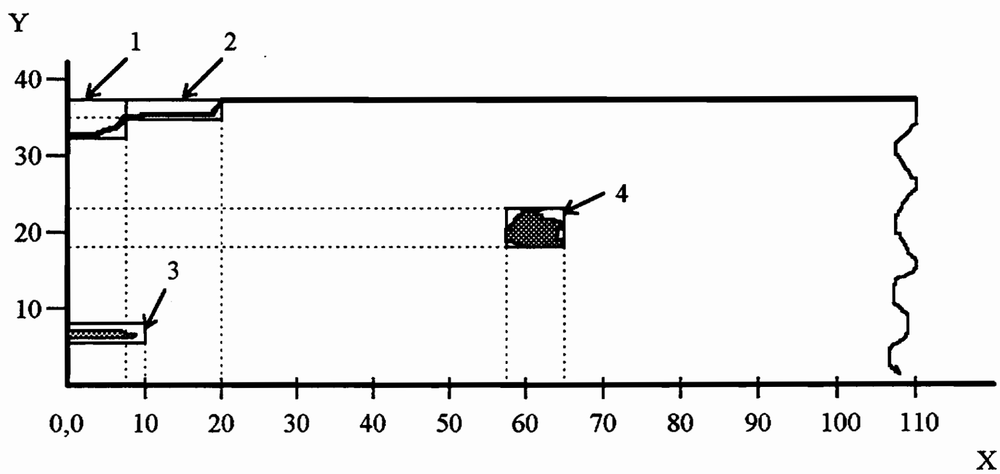



Figure 7. Top view of digitizing table for board face 2 (Anderson et al. 1992).




| Defect No. | $Y_1$ - $X_1$ | $Y_2$ - $X_2$ | Defect Code |
|---|---|---|---|
| 1. | 32 - 0 | 37 - 7 | 8 |
| 2. | 35 - 7 | 37 - 20 | 8 |
| 3. | 6 - 0 | 8 - 10 | 24 |
| 4. | 18 - 57 | 23 - 65 | 12 |

1 unit = 0.25 inch

Figure 8. Digitizing procedures for recording defects.

Defects on the opposite face are recorded by flipping over the board to the upper side of table (see Figure 7). The digitizer is then set with a new origin with coordinate (0,0) to represent the reversal of faces. In this position, the digitizer works in the -Y, +X quadrant mathematically. The dimension of a defect is physically measured by pointing the digitizer wand at the upper left corner of a bounding rectangle for $Y_1$-$X_1$ coordinate and pointing the digitizer wand at the lower right corner of bounding rectangle for $Y_2$-$X_2$ coordinate. To ensure perfect defect registration with the front face of the board (face 1), the digitizer automatically converts the -Y dimensions to +Y dimensions for the back face of the board (face 2).

Rounding down occurs when the defect location does not fall on an exact grid line (Anderson et al. 1992). The rounding is used to get the proper spatial relationship between defects and the board line. To avoid rounding down to zero, Anderson et al. (1992) employs a technique that preserves defects with Y and X dimensions 1/4 inches or less. This same technique is used in the digitization of lumber data in the research.

Defect types are recorded using an adoption of the code system employed by Gatchell et al. (1992) in the red oak data bank. Table 1 gives the defect list and their codes.

The total data for each board includes: a board label, Y-X coordinates defining the minimum bounding rectangle that encloses the board, the board face on which the defect is located, and the defect type code (see Table 2). For example, the third data line in Table 2 shows the coordinate (0-0 35-580) to represent the bounding rectangle of the board. The remainder of the data lines are a description of the lumber defects: the first and the second columns are the defect coordinates for the bounding rectangle for each defect; the third column is the face of the board; the fourth column is the defect code.

### 4.4 Automatic Defect Detection

The same 134 boards that are manually digitized are automatically inspected by running them through a prototype machine vision system located at the Brooks Forest Products Center at Virginia Tech. The lumber scanning system is shown in Figure 9. The feeding position of the boards is consistent to the position of the board during manual digitization. The lumber is 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 is established, it is released into the scanning system where a full length color image is collected from the top face of the board. Every board is fed twice because hardware is only available to scan one side per run. Other imaging systems are available such as laser ranging and x-ray but are not used in this study. 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

Table 1. Defect coding systems

| No. | Defect code | Defect description |
|---|---|---|
| 1. | 2 | Void |
| 2. | 3 | Pith |
| 3. | 4 | Decay |
| 4. | 5 | Shake |
| 5. | 6 | Pith - related tear or split |
| 6. | 8 | Wane |
| 7. | 9 | Sawline |
| 8. | 10 | Bark pocket |
| 9. | 11 | Grub hole-diameter 1/4 in and over. |
| 10. | 111 | Shot worm hole - diameter between 1/16 and 1/4 inch. |
| 11. | 211 | Pin worm hole - diameter 1/16 inch or less. |
| 12. | 12 | Unsound knot |
| 13. | 13 | Burl with bark or check |
| 14. | 14 | Surface check |
| 15. | 15 | Sound knot |
| 16. | 16 | Machining defects |
| 17. | 18 | Incipient decay |
| 18. | 19 | Sticker stain |
| 19. | 20 | Bud trace with bark/check. |
| 20. | 22 | Sap stain |
| 21. | 23 | Bird peck |
| 22. | 24 | Split |
| 23. | 25 | Mineral streak |

Table 2. Sample of data format

GRADE 0C BOARD NUMBER 105 TOTAL NUMBER OF DEFECTS 5

MEASURED WIDTH 34

| | | | |
|---|---|---|---|
| 0- 0 | 35-580 | | |
| 6- 26 | 10- 31 | 1 | 12 |
| 17-568 | 18-580 | 1 | 24 |
| 23-234 | 25-236 | 1 | 11 |
| 7- 25 | 11- 30 | 2 | 12 |
| 16-570 | 17-580 | 2 | 24 |

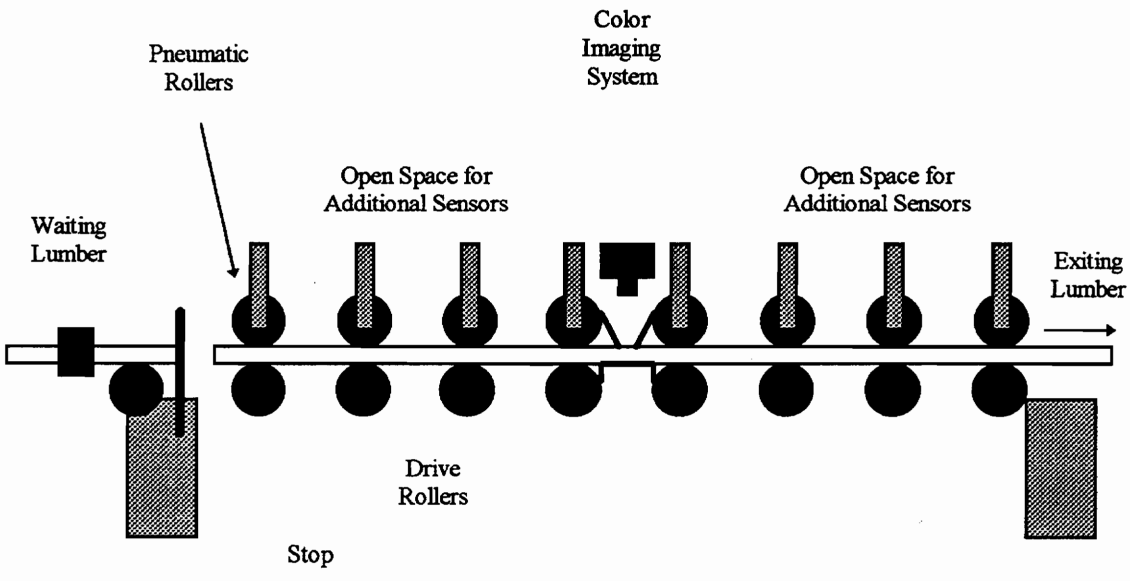



Figure 9. Schematic of lumber handling system configured with color sensor.

fence to keep the board straight, there is no fence available within the scanning system to assure that board straightness is maintained. The scanning process is repeated on the opposite board face. Scanned color images for both faces are stored in the computer for further processing.

Color images for each board are 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 for every board. Data is formatted to match the data format used in the manual digitization process. The scanning system can classify defects in only the following five classes: wane, knot, split, hole, and void. For verification purposes board images are viewed on the computer display. Boards that are not scanned properly (e.g. improper light intensity or other obvious scanning errors) are rescanned to ensure consistent results.

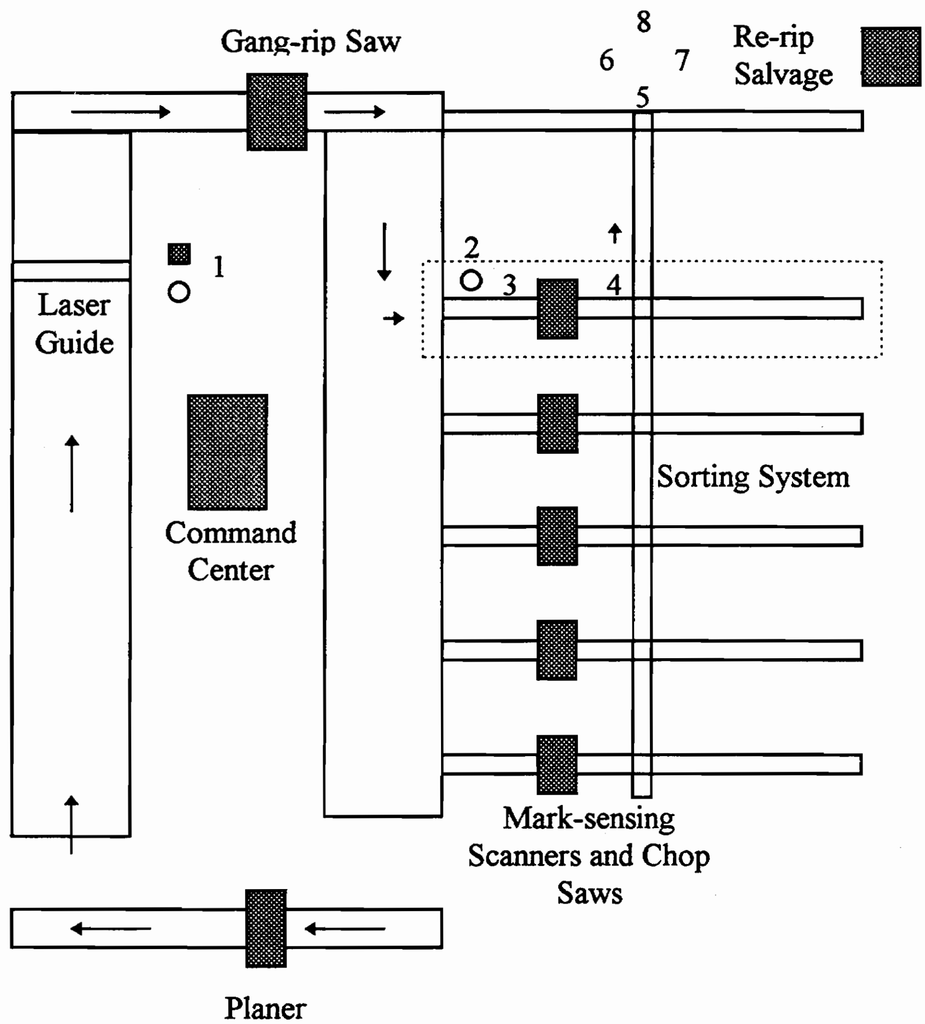
## 4.5 Mill Study

### *4.5.1 Mill description*

The mill study is performed at the Vaughn-Bassett furniture rough mill in Galax, Virginia. The mill studied is a rip-first furniture rough mill system. The lumber processing scheme employed in the mill is semi-automatic including a laser-guided gang-rip saw and a set of automatic cut-off saws. The process is controlled by a Command

Center that optimizes for a specified cutting bill. Optimization employs two independent computer programs: (1) a computer program for maximizing strip yield at the gang-ripping operation and (2) a computer program for optimizing part yield at the chopping operation.

Figure 10 shows the layout of the rough mill system studied. Lumber processing starts with planing the boards and then the boards are conveyed to the gang-ripping station. While being conveyed, the gross width of the board is measured automatically when the board passes under a camera sensor. At the gang-ripping station, the operator defines the usable width of the board with a laser guide. Based on the usable width set by the operator, the optimizing computer controller automatically positions a moveable fence to guide the board through the gang rip saw, so that optimal strip yield is obtained.




**Labels:**

■ : Laser Guide and Gang-rip saw Computer Control

○ : Plant Operator

1-8: Mill Study Personnel

→ : Mill Study Lumber Processing Flow

Figure 10. Vaughn Basset rough mill layout and mill study lumber processing flow.

Strips from the gang-ripping station are then moved to the crosscutting station. In Vaughn Basset there are five crosscutting lines or saws with each having its own computer control program and defect mark scanner. Here, operators examine every single defect on the strips and mark them with fluorescent chalk. Then, the strips run through a mark sensing scanner; the scanner recognizes the position of defects based on the fluorescent chalk marks. Based on data from the scanner, a computer program optimizes part production obtained from the strips according to a cutting bill specified in the Command Center computer. The computer then directs the crosscut saw to chop strips into the desired part lengths.

The next step is part sorting. The parts are automatically sorted according to part size. Here, several operators are employed to inspect the parts for unacceptable defects and recycle them, if necessary, to be re-chopped at the crosscutting line. Parts that need to be re-ripped are sorted separately for re-ripping and sent to a separate manual re-rip salvage saw. Product output and yields are automatically tallied by each crosscut saw and are compiled at the Command Center computer.

### *4.5.2 Research study at the mill*

The same 134 boards which are manually and automatically described in the laboratory are brought to the mill to be processed into furniture parts. To simplify the data collection activity, only one crosscutting line was used. Senior operators with the most experience are selected to make the key cutting decision at the rip saw and chop saw centers. A specific cutting bill for 4/4 red oak lumber is set up at the Command Center (see Table 3). Part quality is specified by the mill as Clear 1 Face. Small unsound defects (maximum size of 0.0625 square inches) are allowed on either face. Sound defects such as mineral streak, sap stain and sound knots are designated to be acceptable defects and are also allowed on either face.

The gang-rip-first rough mill's cutting bill used during the study include three widths and eleven lengths. Table 3 shows the widths, lengths, and quantity of part on the cutting bill. The mill achieves the quantity of parts by selecting part values. For example, all 30" length parts are specified to have a low value compared to the other parts.

The rip saw arbor system used by the mill is a Fixed-Blade-Best-Feed. Under this system, boards are fed into a gang-rip saw with a moveable fence at the left edge of the incoming boards. Based on the widths required in the cutting bill, the mill sets up the blades on the arbor with nine spacings as follows (in inches, from left to right):

3.00 - 3.00 - 2.50 - 1.75 - 2.50 - 2.50 - 1.75 - 1.75 - 1.75

Table 3. Mill's cutting bill with part distribution

| Width | Length | Number 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 |

Recording of mill data starts at the gang-ripping station. Before the boards are gang-ripped, every board number and processing sequence number is recorded. From the gang-rip saw computer screen, several items are recorded such as gross board width, usable board width, and number of strips obtained from each board. Then, every strip generated from a board is numbered with a sequence number code based on the processing order.

Similarly, parts generated at the chop saw are collected and numbered based on their position in each strip. The research study does not run automatic sorting so that all parts could be collected in sequence as they are cut from strips. Therefore, parts were collected only at one sorting station. All parts are gathered and brought back to the Brooks Center Laboratory for further examination. Because of limited time at the mill, the pieces that have to be re-ripped and re-chopped are not processed in the mill. Salvage part sizes from re-ripping and re-chopping are estimated in the laboratory. In the laboratory, parts are grouped according to the original board and the actual observed yield of every board is calculated.

This mill study requires eight people to handle all phases in collecting data. Figure 10 illustrates the data collection activity and is summarized below:

1. Person #1 records the board number, gross width, usable width, number of strips, and board rip yield.

2. Person #2 marks the strips with codes according to sequence number. For example 1A, 1B, 2A, 2B, 2C etc. The numeric code represents the sequence number of board and the alphabetic code represents the sequence number of the strip from each board.
3. Person #3 marks the surface of pieces that are to be re-ripped with a slash mark. This person verifies that the marked strip number would not be in a discarded portion of the strip. This person also makes sure that the previous strip has cleared the chop saw before queuing up another strip.
4. Person #4 makes sure that pieces are on the belt in proper order (prevented mixing of pieces). This person maintains obvious gaps between strips if strips are processed without delay.
5. Person #5 takes pieces off the belt and groups the pieces in a sequential order with the strip code showing to make it easier for persons 6 and 7 to code them. This person sometimes is busy and needs assistance from 6 or 7 to off load pieces from the belt.
6. Person #6 and #7 code mark pieces in order as they come out of the strip. (mark with codes 1A1, 1A2, 1A3, etc.)
7. Person #8 stacks pieces on a pallet as close to sequential order as possible. Pieces with slash mark are sorted separately to be re-ripped.

All system variables impacting yield such as cutting bill, arbor setup, and part priorities are recorded. A summary report from the Command Center is also obtained for verification purposes.

### 4.6 Simulation Experiment

Using ROMI-RIP (Thomas et al. 1995), lumber data generated from both manual digitization and automated defect detection are cutup using similar variables observed in the mill. Those variables consist of cutting bill, arbor type, blade spacing on the arbor, and allowable defects on the parts. The same arbor configuration is simulated in ROMI-RIP. As mentioned earlier, the saw arbor type is Fixed-Blade-Best-Feed with nine spacings from left to right: 3.00-3.00-2.50-1.75-2.50-2.5-1.75-1.75-1.75.

The mill's cutting bill including quantity of obtained parts is setup for the ROMI-RIP simulations (Table 3). To avoid the production of parts not specified in the cutting bill, desired quantities are set slightly higher than that obtained from the mill with the same percentage.

Complex Dynamic Exponent, a part prioritization strategy that dynamically assigns each part size a priority based on its size and desired quantity, is chosen for ROMI-RIP simulations. This is the best prioritizing strategy that give highest simulation yields with similar distribution to the observed distribution (see Table 4).

Table 4. Yield test of prioritization strategies available on ROMI-RIP.

| No. | Prioritization Strategy | Yield (%) |
|---|---|---|
| 1. | Complex Dynamic Exponent | 70.3 |
| 2. | Simple Dynamic Exponent | 69.8 |
| 3. | $L^2$*W*NEED | 68.8 |
| 4. | $L^2$*W | 68.3 |
| 5. | Dynamic Value | 67.3 |
| 6. | Value | 67.3 |

All acceptable defects are excluded from the list of board defects. Those defects include sap stains, mineral streaks, sound knots, and unsound defects with area 0.0625 square inches or lower. DATAMOD, a data modification routine provided by the U.S. Forest Service's Princeton Lab, is used to exclude these defects considered to be acceptable on the parts. Part quality is assigned as Clear 1 Face in ROMI-RIP.

With lumber data scanned from the color camera-based scanning system, there will be occasions when the scanning system will not detect all critical defects present on the lumber. In absence of these defects, ROMI-RIP will generate cuttings that will have unacceptable defects. A C-language analysis routine is developed and used to adjust yields to take these cuttings into consideration. 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 (see Table 2) with the defects that are present on the cutting. All of the defective cuttings generated are then re-run through ROMI-RIP using the same cutting parameters as discussed above to estimate a salvage yield. To prevent ROMI-RIP from unnecessarily reducing the cutting width, the routine also adjusts 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 saw kerf lines, appropriately applied to each edge of the part. The standard ROMI-RIP output is used to determine the affect of undetected defects on part yield.

Simulation output includes board yield, total yield, part distribution, description of primary and salvage yield. To verify the output, all recorded board features with simulation cutting line are displayed on the Cartesian grid system. Obtained parts can be specified for both primary parts and salvage parts.

### 4.7 Yield Analysis

The results of three yield study methods (yield observed at the mill, optimized yield on manual digitization data, and optimized yield on automatic scanning data) are compared to each other. In this study, the yield is presented in the percentage of recovery (sum of part volume generated divided by gross lumber volume). Based on the obtained yield, Chapter 5 discusses the relative yield performance of color-based machine vision system compared to both the observed yield in the rip-first rough mill and the optimum yield based on manual digitization data.

## Chapter 5

# 5.0 RESULTS AND DISCUSSION

This Chapter presents the results from which the prototype color-based machine vision system can be evaluated. First, results from the mill study will be presented and discussed. Observed yields from the mill study will provide an understanding as to how lumber is processed in a real rough mill environment and will provide a baseline from which optimum and automatic scanned yields can be compared. Second, the ROMI-RIP (Thomas, 1995) simulation results will be presented on both the manually digitized board data (optimum yield) and the automatically scanned board data (scanned yield). In the third part of this Chapter, yields will be compared to highlight the differences between observed, optimum, and scanned yields. Finally, the last section will discuss how well the color-based machine vision system performs and where major errors in the automatic lumber scanning system occurs.

## 5. 1 Mill Study

The total observed yield at the furniture rough mill studied is found to be 65.6 percent. This yield is calculated based on the ratio between total surface area of parts obtained in the rough mill to the total area of lumber that was prepared for the study. The parts generated at the mill consists of both primary parts and salvage parts and are distributed according to part sizes specified in the cutting bill. Appendix 1 lists the observed yield attained for each of the 134 boards processed in this study.

### *5.1.1 Part size distribution measured at the mill*

Figure 11 reveals the part length distribution obtained in the three studies for each width category in the cutting bill (see Table 3). Parts obtained from actual cutting observed in the mill are distributed according to the need specified in the cutting bill. Part quantities "observed" in the mill are used to represent the actual part needs in the "optimum" and "scanned" simulation studies. Based on the number of boards processed, even priority is observed for each width category. However, substantially different priority is observed for part length. For each part width observed in the mill, 16" parts are the most common and 30" parts are the least common. It is noted in the mill's

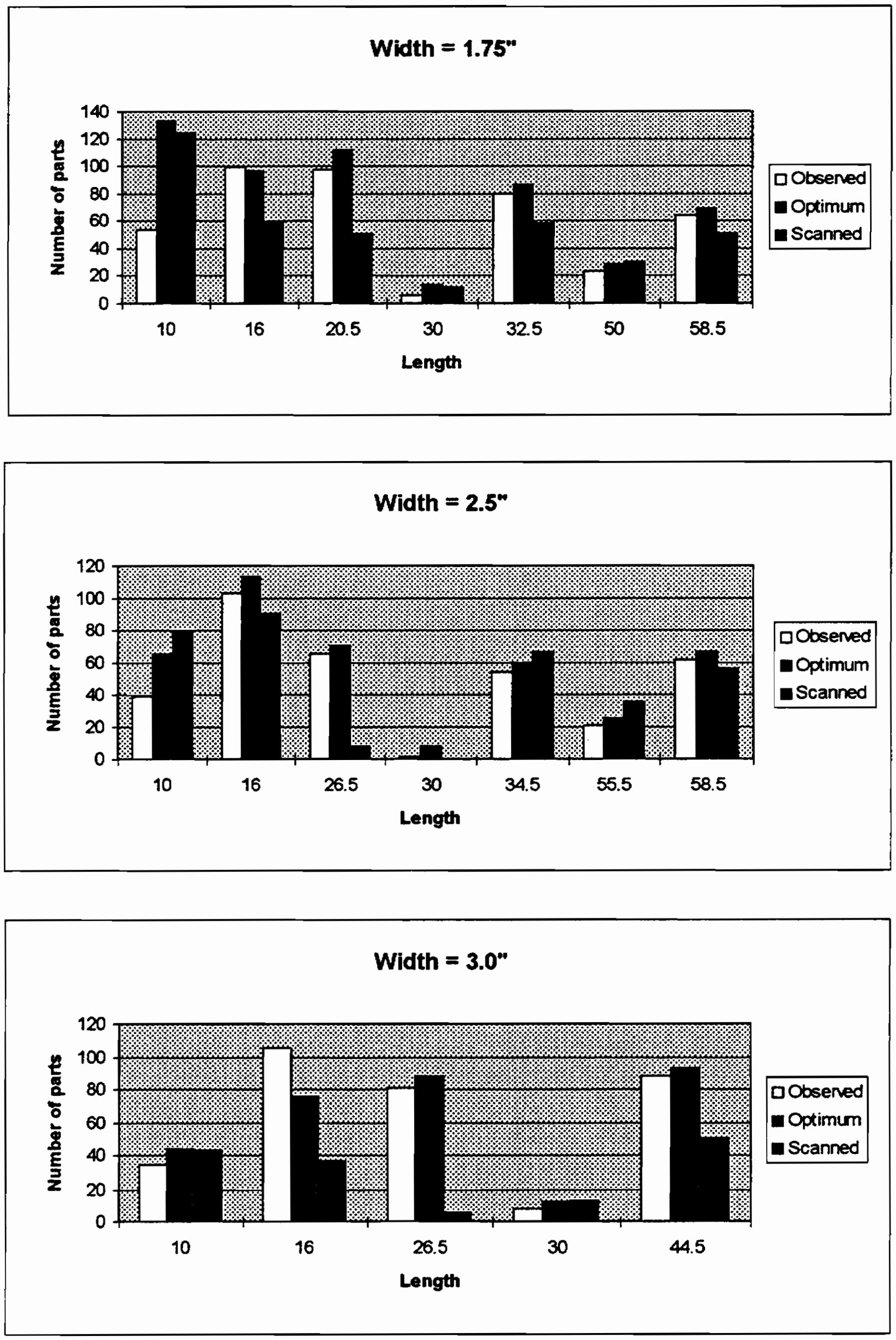



Figure 11. Part length distribution from three yield study methods: observed yield, optimum yield, and scanned yield.

cutting bill at the Command Center that 30" parts were given the lowest cutting priority. This low priority setting is the major reason that there is a low volume of 30" parts

### *5.1.2 Rip saw yields vs. crosscut saw yield*

The observed gang rip saw yield was found to be 81.1 percent. This yield is counted based on the area of the strips generated from the total usable board area. To be consistent with other methods in determining the gang rip saw yield, the usable board area defined in the manual digitization is used. Given the arbor setting and the usable board area, the computer program at the computer assisted gang rip saw in the mill optimizes the yield of strips. The rip saw yield is affected by how the operator sets the laser guide lines, the shape of board (board shape affects the accuracy of the operator in setting the laser guide lines), the width of saw blade kerf, and the saw spacings available on the arbor.

The yield of parts from strips for the observed crosscut sawing operation is found to be 80.9 percent. The crosscut saw yield is calculated based on the area of parts generated from the total area of strips available. This yield includes both primary and salvage part yields and will be discussed in the next section. The operator manually marks defect locations on the strips. Then, a scanner on the optimizing chop saw automatically reads the location of the defect marks and sends the clear strip areas to the computer for optimization. The crosscut yield depends on how good the operator can recognize defects. Knowledge of defect types, patterns, and sizes is important in determining acceptable defects.

### *5.1.3 Primary yield vs. salvage yield*

As stated earlier, the total mill yield is observed to be 65.6 percent. From the observed total, primary yield and salvage yield are found to be 62.2 percent and 3.4 percent, respectively. Total primary yield is calculated based on the total primary part area generated from the entire lumber sample area. A primary part is defined as an acceptable defect free part that is generated after one rip operation and one crosscut operation. Total salvage yield is based on the total salvage part area generated from the entire lumber sample area. A salvage part is defined as a part obtained from reprocessing rejected parts (additional rip and/or chop saw operations) that contained unacceptable defects or unmet size requirements.

A total of 143 parts are produced in the rough mill that had unacceptable defects. All of these parts could be re-processed with additional sawing to produce salvage parts. The original and salvage volume of these parts are 45.2 bd. ft. and 30.5 bd. ft., respectively, indicating that 67.5 percent of the parts volume could be salvaged. In this research, salvage is estimated visually in the laboratory for the next largest size part (length and width) obtainable from the piece. Salvage parts are realized by three possible salvage reprocessing operations: re-rip only, re-chop only, and both re-rip and re-chop. The summary of salvage yield from the three reprocessing scenarios is shown in Table 5.

Table 5. Salvage yield based on three different types of reprocessing.

| Re-rip (percent) | Re-chop (percent) | Re-rip and Re-chop (percent) | Total Salvage (percent) |
|---|---|---|---|
| 1.7 | 1.4 | 0.3 | 3.4 |

### *5.1.4. Role of defects on actual cutting*

Defect area for each type of defect is counted based on data obtained from the manual digitizing (Table 6). The area is counted by summing area for each unacceptable defect type on both sides of the lumber. The purpose for counting defect areas is to give an indication of what type of defect may have the most significant impact on the cutting decision. In this study, assessing the effect of defects is based on an assumption that larger total defect areas causes more difficulties during the marking process. Table 6 shows that void has the largest area followed by wane, unsound knots, splits, and bark pocket. 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 rip saw process.

Table 6. Defect areas observed on the lumber specimens

| No. | Defect Types | Area (sq.in.) |
|---|---|---|
| 1. | Void | 7592 |
| 2. | Wane | 1909 |
| 3. | Unsound knot | 1223 |
| 4. | Sap stain | 963 |
| 5. | Mineral streak | 794 |
| 6. | Split | 442 |
| 7. | Bark pocket | 354 |
| 8. | Machining defects | 105 |
| 9. | Hole | 82 |
| 10. | Sound knot | 75 |
| 11. | Saw line | 22 |
| 12. | Decay | 19 |
| 13. | Bud trace | 12 |
| 14. | Surface check | 9 |
| 15. | Shake | 7 |
| | Total Area: | 13,608 |

Table 6 lists all lumber features observed on the lumber, even those feature that were considered acceptable to the mill. The total area of these features are 13,608 sq. in. or approximately 12.3 percent of the total board surface area. Recall that sound knots, sap stain, mineral streak, and other unsound defects with areas of 0.0625 sq. in. or lower were deemed as acceptable defects. The total area of unacceptable features is 11,767 sq. in. or about 10.7 percent of the total board area. By deeming these certain features as acceptable, an additional 1.6 percent of the total volume of lumber can be used to produce cuttings.

The occurrence of unacceptable defects on primary parts is related to (1) the frequency of occurrence of the given defect type, (2) operator strategies for realizing maximum yield, and (3) the difficulty associated with detecting the presence of a particular defect type. As shown in Table 7, wane is the major defect remaining on the parts that required salvage operation. Wane is typically left on the parts intentionally because the gang rip saw is unable to rip the entire edge containing wane without a significant loss in yield. The second major reason for reprocessing parts is unmet width size. Board crook and taper, which is described as a void defect, contribute to the unmet size of width. In the rough mill, parts containing wane or unmet width size are re-ripped at a separate manual rip-saw salvage operation. This salvage operation is planned in an attempt to achieve greater yield. Therefore, salvage operations due to wane and unmet size, in general, cannot be attributed to operator error.

The remainder of defect types (defects 3-7 in Table 7) have a negative impact on yield and result largely from operator marking error. Accurately marking unsound knots is the main difficulty faced by the human operator. Another difficulty is found in identifying splits. Problems in identifying knots and splits arise due to the fact these defects occur most frequently (see Table 6). Because holes, bark pockets, and decay occur with a much smaller frequency (Table 6), less rework was needed to remove these defects from rejected primary parts. A detailed description of unacceptable defects left on cuttings and the associated reprocessing of each piece of wood is presented in Appendix 2.

Table 7. Frequency of defects left on rejected parts needing rework.

| No. | Type of Defect | Frequency |
|---|---|---|
| 1. | Wane | 57 |
| 2. | Unmet width size | 42 |
| 3. | Unsound knot | 26 |
| 4. | Split | 17 |
| 5. | Hole | 4 |
| 6. | Bark pocket | 2 |
| 7. | Decay | 1 |

### *5.1.5. Concluding Remark*

The total observed yield at the mill is 65.6 percent, consisting of 62.2 percent primary yield and 3.4 percent salvage yield. Obtained parts are distributed in part sizes according to the need specified in the cutting bill. In the present operation of rough mill system, the role of the human operator is very important. The critical points found in the mill study is setting the laser guide lines for usable lumber width and marking strips for unacceptable defects. Mistakes in these critical activities not only cause a reduction in yield but also cause additional reprocessing costs.

## 5.2 Computer Simulation

The results of computer simulation on both manually digitized lumber data and scanned lumber data is presented in this section. ROMI-RIP, a simulation program for gang rip first cutup operations, is used in this study. Similar variables as observed in the mill are applied to the ROMI-RIP simulations for lumber cut up.

### *5.2.1 Optimum Yield*

The optimum yield from the same set of lumber is found to be 69.1 percent. Optimum yield is defined as the yield obtained from computer simulation using manually digitized lumber data. As stated earlier, data generated from manual digitization is assumed to be complete data representing all surface features of the lumber so that the yield obtained from simulation on this data is considered to be "optimum" or the best possible yield that can be attained from the 134 board sample. Therefore, the optimum yield is used as a reference in assessing the performance of rough mill operation and color-based machine vision system. Appendix 1 lists the optimum yield for each board in the lumber sample.

#### *5.2.1.1 Part size distribution*

As mentioned earlier, the optimum yield is found by simulating the actual rough mill condition as closely as possible. Figure 11 reveals the distribution of parts associated with optimum yield in the three width categories for different lengths. When comparing optimum parts distribution with the observed distribution in Figure 11, parts obtained from the simulation are distributed similarly to the parts obtained from the mill study because the same cutting bill was used. The only notable difference in optimum yield distribution is the greater number of 10" lengths generated for 1.75 " wide parts.

This difference is due to the simulated salvage operation which predominantly resulted in the shortest, narrowest parts (10" long , 1.75" wide).

*5.2.1.2 **Rip saw yield vs. chop saw yield***

The yield of strips generated from lumber is 85.2 percent and the yield of parts generated from the strips at the chop saw is 81.1 percent. By comparison, the strip yield measured in the mill study is 81.1 percent and the part yield generated at the chop saws is 80.9 percent.

*5.2.1.3 **Primary yield vs. salvage yield***

In this study, simulation on manually digitized lumber yields 67.4 percent and 1.7 percent of primary yield and salvage yield respectively. Appendix 1 reveals primary and salvage yield for each board. In the simulation process, after gang-ripping, ROMI-RIP examines the clear area of the strips for attaining full-width primary part length. ROMI-RIP considers the specified sizes and desired quantity in optimizing primary yield. The remaining strip area is examined for salvage parts.

### *5.2.2 Scanned yield*

The scanned yield from the same 134 board sample is found to be 49.0 percent, the lowest of the three yield scenarios. Scanned yield is defined as yield obtained from computer simulation using automatically scanned lumber data. ROMI-RIP is used to simulate the same set of actual conditions as used in the mill. Appendix 1 lists the scanned yield for each board in the lumber sample. The relatively low yield generated from the scanned data is due to automatic defect detection errors. The reasons behind the lower yield performance of the color-based machine vision system will be assessed in a later section.

#### *5.2.2.1 Part size distribution*

Obtained parts are distributed according to part length in three different width categories. Figure 11 shows the distribution of part length from scanned yield in comparison with observed yield and optimum yield. In general, scanned yield cannot match the number of cuttings in the observed mill. Number of cuttings are particularly deficient in wide parts (width = 3.0 inches). The lower recovery of cuttings is attributed to a smaller amount of usable clear area on the scanned boards due to falsely detected defects. The affect of these falsely detected defects on yield will be discussed in greater detail later.

#### *5.2.2.2. **Rip saw yield vs. chop saw yield***

The yield of strips generated from lumber is 71.9 percent and the yield of parts generated from strips is 68.1 percent. Compared to the previous yields, these yields are the smallest.

#### *5.2.2.3. **Primary yield vs. salvage yield***

From the total yield of 49.0 percent, primary yield is found to be 40.4 percent and salvage yield is 8.6 percent. Appendix 1 reveals the primary and salvage yield for each board. Compared to the previous total yields (observed and optimum), this primary yield for the scanned boards is the smallest and the salvage yield is the largest by far. The relatively large salvage yield is due to the fact that the scanning system sometimes does not detect all of the unacceptable defects (a false negative) on lumber. This defect detection error causes an excessive number of parts to be reworked through additional salvage operations. Appendix 3 shows the effect of this defect detection error on salvage yield. The effect of this type of defect detection error (i.e. failure to detect all unacceptable defects) on total yield will be discussed in greater detail later.

#### *5.2.2.4. Role of defects on automatic cutting*

As mentioned above, the scanning system does not detect all of the unacceptable defects on lumber. The affect of this error is considered by using a C-based analysis routine to determine which parts have unacceptable defects and then estimate how much volume can be salvaged from the defective parts. The frequency of defects left on the parts generated based on the scanned lumber data can be used as an indicator as to how defect types affect the scanning process. Table 8 shows the frequency of defect types found on parts needing rework.

Table 8. Frequency of defects left on rejected parts needing rework.

| No. | Type of Defect | Frequency |
|---|---|---|
| 1. | Unsound knot | 49 |
| 2. | Split | 41 |
| 3. | Bark Pocket | 34 |
| 4. | Wane | 10 |
| 5. | Void | 4 |
| 6. | Machine defect | 3 |
| 7. | Surface checks | 3 |
| 8 | Sawline | 2 |
| 9 | Decay | 1 |
| 10 | Shake | 1 |

Except for wane and void, note that the scanning system has most difficulty with those surface defects that occur most frequently (see Table 6). Due to material handling problems that make the scanned board appear narrower than it should be, the scanning system does not have difficulty with wane and void detection. However, other problems are associated with material handling errors and will be discussed later. All of the parts that had unacceptable defects and how they were salvaged are listed in Appendix 3.

### 5.3 Concluding remark

Table 9 summarizes the yield found from the mill study (observed) and the optimum found from the simulation based on manually digitized lumber data (optimum) and based on the scanned lumber data (scanned). The scanned yield is found to be the lowest, 16.6 percent lower than the observed yield and 20.1 percent lower than the optimum yield. Several possible sources of error in the color-based machine vision contribute to the substantially lower yield. These sources of error along with other issues will be discussed in a later section.

Table 9. Summary of optimum and observed yield.

| Yield Study Methods | Operation Yields | | | Part Yield | | |
|---|---|---|---|---|---|---|
| | Rip saw (percent) | Chop saw (percent) | Total (percent) | Primary (percent) | Salvage (percent) | Total (percent) |
| 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 |
| Scanned | 71.9 | 68.1 | 49.0 | 40.4 | 8.6 | 49.0 |

### 5.4 Evaluation of the Observed Rough Mill System

As discussed earlier, Table 9 shows the results of the three yield study methods. The total observed yield in the rough mill (65.6 percent) is 3.5 percent lower than the optimum yield. Considering all factors in an actual rough mill environment at production speeds, the observed yield is very close to optimum. However, if this lumber sample is indicative of the mill's long term yield performance, a 3.5 percent potential for yield improvement can save the mill a substantial amount in annual lumber costs

Observed yields are found lower than optimum in both the ripping and crosscutting operations. The largest contributing process to reduction in yield observed at the rough mill is in the ripping operation. Observed rip saw yield (81.1 percent) is found to be 4.1 percent lower than optimum. A major part of this reduction in yield is due to difficulties in establishing the optimum position of the laser guides to define the usable width of the board. In the observed mill, the operator tends to select a usable board width narrower than optimum. Precisely defining the maximum usable width of the board is difficult. For example, it is difficult for an operator to decide at production line speeds whether an 1/8" or a 1/4" increase in board width will gain an extra usable strip or not.

Chop saw yield (80.9 percent) is observed to be 0.2 percent lower than optimum yield. Appendix 2 lists all parts that require rework due to unacceptable defects. A total of 45.2 board feet of parts had to be reworked. This rework volume represents about 8.5 percent of the total volume of parts generated. Salvage operations (re-ripping and/or re-crosscutting) on these parts recover 30.5 board feet or a salvage recovery of about 67.5 percent. In comparison to optimum salvage recovery volume (13.2 board feet), observed salvage recovery volume is 231 percent greater. Although insufficient data was collected to determine precisely how marking inaccuracies affected yield, the substantially higher volume of salvage parts generated in the observed mill will increase manufacturing costs.

## 5.5 Evaluation of Automatic Color Scanning System

As mentioned earlier, the total scanned yield is the lowest (50.8 percent) of the three cut-up "optimization" methods, 16.6 percent and 20.1 percent lower than observed and optimum yields, respectively. There are two possible sources of error observed in the color-based machine vision system in detecting defects: (1) defect detection errors and (2) material handling errors. Each of these sources of error are discussed along with their relative affect on yield performance.

### *5.5.1 Defect detection accuracy*

Based on further examination on the results of defect detection, the color-based system did not detect defects accurately. Defect detection accuracy is measured in terms of false negative error and false positive error. False negative error is defect areas that the scanning system classified as clear wood. False positive error is clear wood areas that the scanning system classified as defect. To assess the effect of false negative and false positive errors on the scanned yield, the scanned data file is systematically adjusted to include defects that are truly present and to remove those defects that are truly clear wood. Void defects are excluded in the analysis of defect detection accuracy. False positive void defects were determined to be almost exclusively associated with material handling and board alignment problems. Material handling errors are discussed in the next section.

Areas relating to both false negative error and false positive error are measured by comparing the lumber features generated by automatic scanning with that of manual digitization. False negative and false positive errors were found to be 1397 sq. in. and 12,909 sq. in., respectively. False negative error and false positive error corresponds to 1.3 percent and 11.7 percent, respectively, of the total lumber surface area (110,334 sq. in.).

Since the area associated with false positive error is quite large (11.7 percent of the board surface area), the affect of this error has a large affect on yield. The affect of false positive error on yield is estimated by removing all false positive areas from the scanned data and re-running ROMI-RIP. The scanned yield with false positive areas removed is found to be 61.4 %. Compared to the original scanned yield, the yield adjusted by removing false positive error is 12.4 % higher. It has been stated in previous research that the color scanning system is very sensitive and tends to identify defects that are truly not present (Conners et al., 1992; Araman and Wiedenbeck, 1995). However, it has not been known until now how this sensitivity affects the magnitude of parts yield that can be attained from lumber.

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, sap stains, sound knots, dirt, or unusual textures/grain patterns on the lumber. The present color-based machine vision system is limited in recognizing feature types. There are five types of features that are currently recognized by the system: wane, knots, holes, splits, and void. If 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 unsound knots are likely features that could generate false positive errors, their affect on potential yield is investigated. This affect is investigated by including mineral streak, sap stain, sound knots, and others (see Table 6) as unacceptable defects in the manually digitized data. When mineral streak, sap stains, sound knots, and all small unsound features are treated as a defects, optimum ROMI-RIP yields dropped by 5.1 percent. Therefore, false positive errors due to a limited feature vocabulary can have a substantial affect on its performance. However, recall that false positive error causes a 12.4 reduction in yield. Therefore, other natural variations in the color of clear wood exist that have a greater effect on the sensitivity of the defect recognition algorithms.

Since the area associated with false negative error is small (1.3 percent of the board surface area), the affect of this error has only a small affect on yield. To confirm this, the affect of false negative error on yield is estimated by removing false positive areas from and adding false negative areas to the scanned data and then re-running ROMI-RIP. The scanned yield with false positive areas removed and false negative areas added is found to be 60.5 percent. Compared to the scanned yield with only false positive areas removed, the yield adjusted by adding false negative error is 0.9 percent lower. The relatively small net change in yield confirms that false negative error has a small affect on yield. However, in terms of parts rework for salvage, false negative errors almost double the volume of parts that have to be reworked (90.9 bd. ft. vs. 45.6 bd. ft.). The increased volume of parts that have to be reworked, although they do not significantly affect overall yield, can substantially increase the manufacturing cost and reduce the number of preferred part sizes. Appendix 3 lists all parts that required remanufacturing due to false negative error.

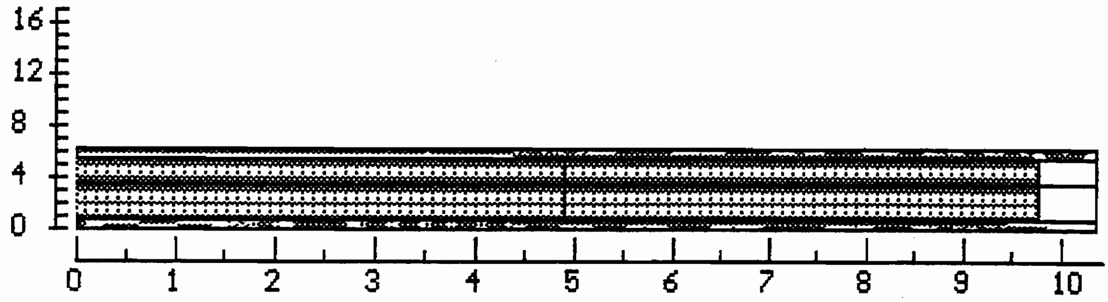
### *5.5.2 Material handling accuracy*

When measuring the coordinates of the board and defect locations, the position of the board is very important. The ideal position of the board is parallel to the X axis when the image of board is displayed. The scanning system used in this evaluation does not always maintain perfect straightness of the board at all times while it travels through the system. In the present material handling system, the machine handles boards using a pinch roller system without a fence or guide to keep boards running straight. The material handling problem occurs especially on boards that have uneven thickness for the entire board, on boards that are twisted, crooked or with other odd shapes.

The affect of a board not running straight through the system can have a substantial affect on yield. Figures 12 and 13 illustrate how board no. 166 in a skewed (non-straight) scanning position reduces the width of strips. The skew of the board causes a potential 2.5" strip to be reduced to 1.75". The problem of board skew through the material handling system is compounded when different board faces have different skew. As stated earlier, the scanning system can only image one face of the lumber at a time. Often times, the position of the board when scanning face 1 and face 2 will likely not be oriented exactly the same such that the bounding rectangle of face 1 does not exactly coincide with the bounding rectangle of face 2. In fact, the position of the board during scanning varied in a mostly unpredictable manner. To illustrate this effect with board no.141 (Figure 14), different orientations between face 1 and face 2 reduces the effective usable width of the board.

Scanning position of board without cutting line


Scanning position of board with cutting line

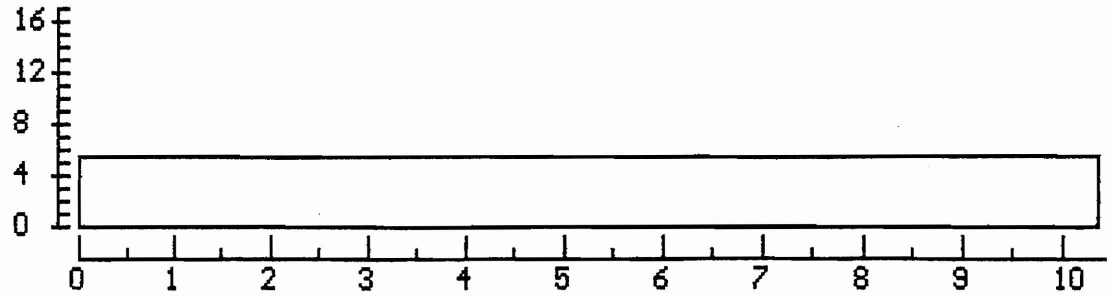



Width: - strip 1 = 2.5”

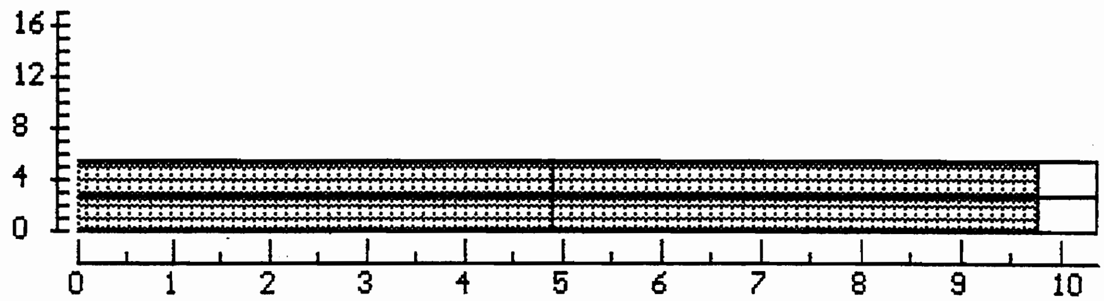
Width: - strip 2 = 1.75”

Figure 12. Board sample no.166 in scanning position with and without cutting line.

Corrected position of board without cutting line




Corrected position of board with cutting line




Width: - strip 1 = 2.5”

Width: - strip 2 = 2.5”

Figure 13. Board sample no.166 in parallel position with and without cutting line.

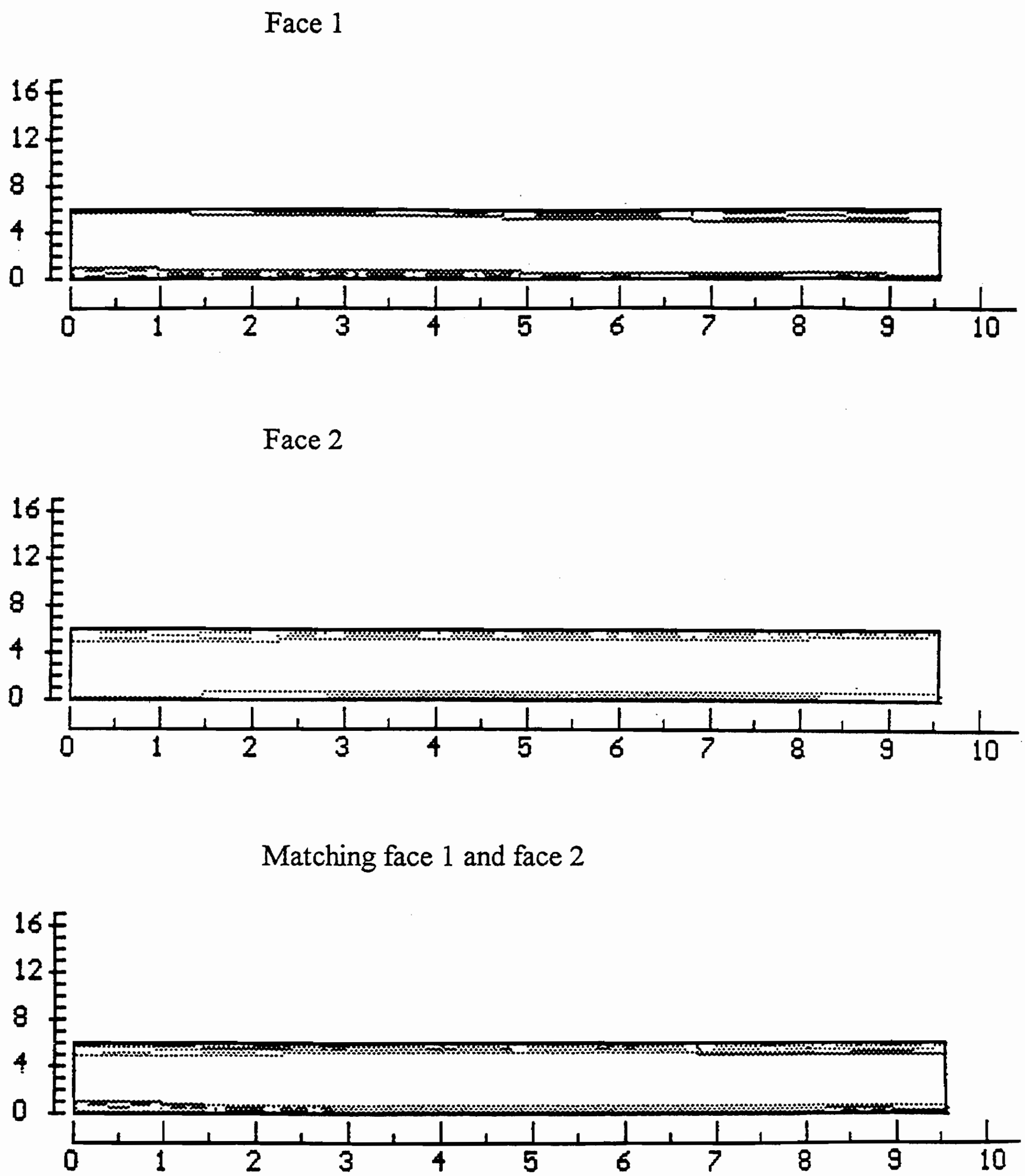



Figure 14. A case found in board sample no. 141 when scanning position of face 1 does not match scanning position of face 2.

To assess the potential effect of board position on yield, the affect of false positive "void" errors on yield is estimated. As mentioned earlier, false positive void errors are exclusively associated with material handling errors. By removing false positive "void" areas from the scanned data and re-running ROMI-RIP, the impact on yield can be studied. The scanned yield with all false positive areas removed, including void, and false negative areas added is found to be 67.8 percent. Compared to the scanned yield with "non-void" false positive areas removed and false negative areas included (60.5 percent), the yield adjusted by adding false negative "void" error is 7.3 percent greater.

Another way to illustrate the problem of material handling is by comparing the yield at the rip saw for both optimum and scanned simulations. The optimum and scanned rip saw yield is 85.2 percent and 71.9 percent, respectively (see Table 9). Hence, the scanned yield is 13.3 percent less than the optimum yield at the rip saw. This is due to the problem of the material handling system in maintaining board straightness. This problem translates into generating a substantial amount of false negative area associated with wane that reduces usable board width and results in a total yield reduction that is substantial.

Attempts are made to correct board skew and adjust for size variations in the software to get a more accurate validation of the performance of the lumber scanning algorithms. However, modification to the ROMI-RIP data file to adjust for board skew introduces other sources of error in the location and size of defects. This error is due to the fact that ROMI-RIP data is modeled as rectangles with 1/4" resolution. Rotation of the board to adjust for skew cause some inaccurate changes in the location and size of a defect due to a lack of precision. However, since material handling errors manifest themselves in many different ways, board rotations were kept at a minimum. A more precise way to adjust for material handling error is to incorporate a rotational algorithm in the original defect detection algorithm. Incorporating an accurate and consistent rotation algorithm is not a trivial task and, hence, will be left for future research if deemed necessary. It is important to note that more precise material handling systems can be designed for future systems to avoid the board skew problem altogether.

One final note, scanned yield (67.8 percent) based on modified data with all false positive areas removed, including void, and false negative areas added is 1.3 percent less than optimum yield (69.1 percent). 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 for two reasons. First, 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 more rectangles than is typically done manually. Therefore, the two sets of data are somewhat different. The second reason is related to a limitation in ROMI-RIP. Since ROMI-RIP can handle up to 200 defects per board, several boards used to estimate the modified scanned yield exceeded this limitation. In these cases, defects were truncated to 200. While errors associated with this truncation affected much less than 1 percent of the total board surface area, it does have some impact on how ROMI-RIP arrives at an optimum solution. Note that this truncation error only occurred with the modified scanned data and not with the original scanned data set used in the yield performance comparisons. In summary, the 1.3 percent difference in yield can be attributed to differences in data digitization and truncation error. However, this difference will have very little impact, if any, on the conclusions regarding where errors occur in the color-based scanning system.

### *5.5.3 Concluding remark*

For 134 lumber test specimens, the overall yield on color-based machine vision system is found to be 49.0 percent. This yield is 16.6 percent and 20.1 percent less than the yield observed at the mill (65.6 percent) and optimum (69.1percent), respectively, for the same set of lumber. The substantially lower yield for the machine vision system is caused by 2 primary sources of error: 1) defect detection error and 2) material handling error. When compared to optimum, losses in yield for the machine vision system are estimated to be reduced by approximately 11.5 percent due to errors in defect detection accuracy and 7.3 percent due to errors in material handling. If these errors can be corrected, scanned yield will increase to 67.8 percent which is higher than that observed in the mill. The remaining 1.3 percent of the yield loss is attributed to data digitization and truncation errors. Of these errors, it is reasonable to assume that problems with material handling, data digitization, and truncation can be readily solved with existing technologies. Even so, the yield performance with such problems solved (59.4 percent) is still substantially less than the yield performance of the observed mill. Therefore, future research should focus on improving the accuracy of feature recognition in lumber.

Chapter 6

# 6.0 SUMMARY AND CONCLUSIONS

## 6.1 Summary

For several years, color-based 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-based machine vision systems can compete in the current state-of-the art. Therefore, the purpose of this study is to rigorously evaluate the performance of color-based machine vision systems for lumber processing applications in the furniture rough mill.

The color-based machine vision system tested is a system 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 defect present within the lumber. The machine vision system is compared to an existing state-of-the-art rip-first rough mill facility that uses a laser-guided gang-rip saw and a series of semi-automatic chop saws that can automatically determine the location of defects based on operator placed crayon marks.

134 red-oak lumber specimens, marketed as 1 Common NHLA graded lumber, were 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 machine vision system resulting in a machine description of the same features obtained through manual digitization.

The lumber specimens were prepared and cut up in the rough mill as clear 1-face furniture parts of specified widths and lengths which were typically produced at the mill. A rough mill data collection procedure was developed such that resulting yields could be traced back to each individual lumber specimen. Observed yields were recorded at the mill and later verified for consistency and accuracy in the laboratory. Specific details are included in this study on the procedures from which future yield studies can be performed in furniture rough mills

Both the manually digitized lumber data and the machine vision scanned lumber data are analyzed using ROMI-RIP, a rip-first rough mill simulation software package. Similar conditions as observed in the rough mill such as cutting bill specifications, arbor set-up, cutting priorities, and desired part quality were included in the ROMI-RIP analysis. The analysis is based on two sets of yield information, one representing optimum yield or the best yield that can be attained for the given set of lumber and the other representing the scanned yield or the yield that would be attained for a color-based machine vision system. In this study, the yield is presented in the percentage of recovery (sum of part volume generated divided by gross lumber volume). Table 10 summarizes the yields attained for each of the study methods.

Table 10. The summary of optimum and observed yield.

| Yield Study Methods | Operation Yields | | | Part Yield | | |
|---|---|---|---|---|---|---|
| | Rip saw (percent) | Chop saw (percent) | Total (percent) | Primary (percent) | Salvage (percent) | Total (percent) |
| 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 |
| Scanned | 71.9 | 68.1 | 49.0 | 40.4 | 8.6 | 49.0 |

The total observed yield at the mill that is 65.6 percent, consisting of 62.2 percent primary yield and 3.4 percent salvage yield. The observed gang rip saw yield is observed to be 81.1 percent and yield at the chop saws is 80.9 percent. Obtained parts are distributed in part sizes according to the need specified in the cutting bill. In the present operation of rough mill system, the role of the human operator is very important. The critical points found in the mill study is setting the laser guide lines for usable lumber width and marking strips for unacceptable defects. Due to frequent occurrence of crook and wane on lumber, accurately setting the laser guide lines in front of the gang rip saw is the main difficulty faced by the human operator. Also, the presence of knots and splits on strips, causes difficulties in accurately marking strips in front of the chop saw. Mistakes in these critical activities not only cause a reduction in yield but also cause additional reprocessing costs.

The optimum yield from the same set of lumber is found to be 69.1 percent, consisting of 67.4 percent primary yield and 1.7 percent salvage yield. Part sizes obtained in the optimum yield are distributed similar to those in the observed. In attempts to achieve optimum yield, a somewhat greater number of smaller cuttings (10" length, 1.75 " width) were generated when compared to observed cuttings. The yield of strips generated from lumber is 85.2 percent and the yield of parts generated from the strips at the chop saw is 81.1 percent.

The scanned yield from the same 134 board sample is found to be 49.0 percent, the lowest of all yield scenarios. From the total yield of 49.0 percent, primary yield is found to be 40.4 percent and salvage yield is 8.6 percent. The relatively large salvage yield is due to the fact that the scanning system sometimes does not detect all of the unacceptable defects on lumber. This defect detection error causes an excessive number of parts to be reworked through additional salvage operations. In general, scanned yield cannot match the number of cuttings in the observed mill. In particular, the number of wide cuttings (width = 3.0 inches) are substantially below that recovered in the "optimum" study. The lower amount of cuttings is attributed to a smaller amount of usable clear area on the scanned boards due to many falsely detected defects. The yield of strips generated from lumber is 71.9 percent and the yield of parts generated from strips is 68.1 percent.

There are several possible sources of error in the color-based machine vision system: (1) the scanning test device can not maintain perfect straightness when board goes through the system, (2) defect classification algorithm causes errors in correctly detecting defects, and (3) data digitization errors are caused due to the different way machines and people digitize areas of defects.

## 6.2. Conclusions

### *6.2.1. Conclusions regarding the furniture rough mill*

Based on the results of the study, the following conclusions are drawn. Conclusions regarding the observed furniture rough mill include:

1. The total observed yield in the rough mill (65.6 percent) is 3.5 percent lower than the optimum yield.

2. A 3.5 percent potential for yield improvement can save the mill a substantial amount in annual lumber costs if this lumber sample is indicative of the mill's long term yield performance.
3. The largest contributing process to reduction in yield observed at the rough mill is in the ripping operation where observed rip saw yield (81.1 percent) is found to be 4.1 percent lower than optimum.
4. The observed chop saw yield (80.9 percent) is observed to be 0.2 percent lower than optimum yield.
5. Over 230 percent more salvage part volume was measured in the rough mill study which can lead to higher processing costs.

### *6.2.2 Conclusions regarding color-based scanning system:*

1. The yield from the scanning system is the lowest (49.0 percent) among the yield study methods, 16.6 percent and 20.1 percent lower than observed and optimum yields, respectively.
2. When compared to optimum, losses in yield for the machine vision system are estimated to be reduced by approximately 11.5 percent due to errors in defect detection accuracy.

3. False positive defect detection errors (actual clear wood areas classified as defect) is the primary cause in scanned yield reduction and is caused by acceptable lumber features that tend to be darker than clear wood (e.g. mineral streak, sap stains, sound knots, dirt, or unusual textures/grain patterns).
4. False negative defect detection errors (actual defect areas classified as clear wood) has very little effect on yield but doubles the volume of salvage parts generated.
5. When compared to optimum, losses in yield for the machine vision system are estimated to be reduced by approximately 7.3 percent due to errors in material handling.
6. When compared to optimum, losses in yield for the machine vision system are estimated to be reduced by about 1.3 percent due to data digitization and defect truncation errors.

Of all the problems that contribute to the inadequate performance of the color-based scanning system, it is reasonable to assume that problems with material handling, data digitization, and truncation can be readily solved with existing technologies. Even so, the yield performance with such problems solved (59.4 percent) is substantially less than the yield performance of the observed mill (65.6). Therefore, future research should focus on improving the accuracy of feature recognition in lumber.

Chapter 7

# 7.0 IMPLICATION FOR FUTURE RESEARCH

This study shows that color-based scanning, in its present state, lacks the precision and accuracy needed to maximize total yield in a furniture rough mill setting. The image processing and defect recognition algorithms employed in this study are "state-of-the-art" in terms of general image processing research. However, these image processing algorithms do lack fundamental knowledge about how all of the wood features, those important to the value of furniture cuttings, manifest themselves in color image data. Some research has been performed on characterization of wood features using color (e.g. Lebow et al., 1996 and Brunner et al., 1990) that can be included in to improve the defect recognition algorithm. It is important to note that adding fundamental knowledge to color-based algorithms must be inexpensive, both in terms of scanning system cost and processing time, if it is to be useful in real-time rough mill automation applications. Still, there is a limit to what can be done in color in creating a robust scanning system (Szymani and McDonald, 1981; Conners et al., 1992). This limit has led to research in developing multi-sensor systems.

The baseline results from this study will be a very valuable to guide the further development of machine vision systems as well as to the further development of the state-of-the-art in furniture rough mill systems. Based on the result that computer optimization found a potential for 3.5 percent higher yield than the observed at the mill, there is an area for improving technology in lumber processing. Further studies and research directions based on the findings of this study include the following topic areas:

1. In-plant testing of more automated state-of-the-art technology for rip sawing systems such as the DYSYS system (Ferrar, 1996) can be performed. The results of this study indicate that the largest loss in the observed system was in the manual placement of the laser guides for the gang rip saw. The DYSYS system uses vision technology to automate this process.
2. In-depth studies can be conducted as to how plant operators mark defects on strips and how this affects yield. The parts generated from this research can be used to re-construct the board from which they were generated. The precise location and type of those features that are eliminated from as well as those features allowed to remain on a part can be studied in much greater detail.
3. The effect of integrating rip-sawing operations with crosscut-sawing operations on yield can be tested. Present state-of-the-art systems do not completely

integrate these operations. Simulations can be used to theoretically test this effect and verified with in-plant studies.

4. "False positive" and "false negative" defect detection errors can be related to the surface color characteristics in wood. Knowledge can be generated to improve the performance of color-based scanning systems. Any modifications to the color-based algorithms can be validated on the same set of data used in this study to observe the marginal performance gain.
5. The performance of an x-ray-based scanning system can be evaluated. In this study, x-ray images were collected on the same boards. Once an image processing algorithm is established based on x-ray images, the same procedures and data established in this study can be used to study how well x-ray scanning performs.
6. The performance of a multiple sensor scanning system that combines both color and x-ray images can be evaluated. Once an image processing algorithm is established based on combining color and x-ray images, the same procedures and data established in this study can be used to determine how well multiple sensor scanning performs.

# LITERATURE CITED


Anderson, R.B., R.E. Thomas, C. J. Gatchel, and N.D. Bennett. 1993. Computerized technique for recording board defect data. Res. Pap. NE-671. Radnor, PA: U.S. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station. 17 p.

Araman, P.A. 1978. A comparison of four techniques for producing high-grade furniture core material from low-grade yellow-poplar. USDA. Forest Service Research Paper NE-429. Northeastern Forest Experiment Station, Upper Darby, PA.

----------------, D. L. Schmoldt, T.H. Cho, D. Zhu, R.W. Conners, and D. E. Kline. 1992. Machine vision systems for processing hardwood lumber and logs. AI Applications 6(2):13-26.

----------------, and J.K. Wiedenbeck. 1995. Test of the Center for Automated of Hardwoods Auto-Image Detection and Computer-Based Grading and Cutup System. In Proceedings from the 2nd International Seminar/Workshop on

Scanning Technology and Image Processing on Wood. Skelleftea, Sweden, pp 92-105.

Brunner, C.C., M.S. White, F.M. Lamb, J.G. Schroeder. 1989. CORY: a computer program for determining dimension stock yields. Forest Prod. J. 39(2):23-24.

----------------, G.B. Shaw, D.A. Butler, and J.W. Funck. 1990. Using color in machine vision system for wood processing. Wood and Fiber Science. 22(4):413-428.

Conners, R.W., C.W. McMillin, and C.N. Ng. 1985. The utility of color information in the location and identification of defects in surfaced hardwood lumber. Pages XVIII-1 to X VIII-33 in Proceedings, 1st International Conference on Scanning Technology in Sawmilling, Miller Freeman, San Francisco, CA.

----------------, T.H. Cho and P.A. Araman. 1989. Lumber grading with a computer vision system. *In* Proceedings of the seventeenth annual hardwood symposium of the hardwood research council; May 1989, Merrimac, Wisconsin.

-----------------, R.W., T. H. Cho, C. T. Ng, T. H. Drayer, P. A. Araman, and R. L. Brisbin. 1992. A machine vision system for automatically grading hardwood lumber. Industrial Metrology 2:317-342.

Englert, G.H. and D.R. Schumann. 1969. Charts for calculating dimension yield from hard maple lumber. USDA. Forest Service Research Paper FPL-81. Forest Products Laboratory, Madison, Wisc.

Ferrar, R. K. 1996. Application of various technologies to obtain images for lumber evaluation. In Proceedings of CIFAC '96 International Symposium, High Point, N. C., 39-45.

Gatchell, C.J. 1987b. Impact of the rough mill practices on yield. In White, J.C., ed. Easter hardwood: the source, the industry, and the market. Proceedings of symposium, 1995 September. 9-11, Harrisburg, PA. Forest Products Research Society, 146-156.

Giese, P. J. and K.A. McDonald. 1982. OPTYLD; A multiple rip-first computer program to maximize cutting yield. Forest Products Laboratory Research Paper FPL-412, USDA Forest Service.

------------ and J.D. Danielson. 1983 CROMAX; A crosscut-first computer simulation program to determine cutting yield. Forest Products Laboratory General Technical Report FPL- 38, USDA Forest Service.

Hall, S.P., R.A. Wysk, E.M. Wengert, and M.H. Agee. 1980. Yield distributions and cost comparisons of a crosscut-first and a gang-rip-first rough mill producing hardware dimension stair parts. Forest Product Journal. 30(5):34-39.

Hoff, K.G., E.L. Adams, and E.S. Walker. 1991a. GR-1ST Pc program for evaluating gang-rip-first board cut-up procedures. USDA. Forest Service, Northeastern Experiment Station, General Technical Report NE-150, Radnor, PA. pp.16

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

---------------, S. Ruddell, K. Mukherjee, and C.W. McMillin. 1989. Economics of cutting hardwood dimension parts with an automated system. Forest Products J. 39(5):46-50.

---------------, S. Ruddell, and C.W. McMillin. 1990. Industry standards for recognition of marginal wood defects. Forest Prod. J. 40(3):30-34.

Kline, D.E., R. W. Conners, D. L. Schmoldt, P. A. Araman, and R. L. Brisbin. 1993. A multiple sensor machine vision system for automatic hardwood feature detection. *In* Proceedings of the 6th International Conference on Scanning Technology in the Wood Industry, Atlanta, Georgia, pp. 1-11.

Klinkhachorn, P., J.P. Franklin, C.W. McMillin, R.W. Conners, and H.A. Huber. 1988. Automated computer grading of hardwood lumber. Forest Prod. J. 38(3):67-69.

--------------------------------------------------------------------------------------------------

1989. ALPS; yield optimization cutting program. Forest Prod. J. 39(3):53-56.

Lebow, P. K., C. C. Brunner, A. G. Maristany, and D. A. Butler. 1996. Classification of wood surface features by spectral reflectance. Wood and Fiber Science 28(1): 74-90.

Lucas, E.L. and P.A. Araman. 1975. Manufacturing interior furniture parts: A new look at an old problem. USDA, Forest Service Research Paper NE-334, Northeastern Forest Experiment Station. Upper Darby, PA.

Maristany, A.G., C.C. Brunner, and J.D. Anderson. 1990. Effect of an exponential weighting function on random width dimension yields. Oregon State University Corvallis, Ore.

Marszalec, E. and M. Pietikainen. 1993. Colour analysis of defects for automated visual inspection of pine wood. *In* Machine Vision Applications in Industrial Inspection, Frederick Y.Wu, Benjamin M.Dawson, Editors, Proc. SPIE 1907. pp. 80-94.

Mullin. 1990. Why switch to rip-first? Furniture Design & Manufacturing. Sep. pp. 36-42.

National Hardwood Association. 1986. Rules for the measurement and inspection of hardwood and cypress lumber. NHLA, Memphis, Tenn.

Pierson, G. and P. Rieth. 1992. Potential result of using a ripsaw optimizer in furniture manufacturing. *In* Proceedings of First International Symposium on Computers in Furniture and Cabinet Manufacturing. Wood Machining Institute, Atlanta, Georgia.

Regalado, C. 1991. Optimization of edging and trimming operations for red oak lumber. Master's Thesis, Dept. of Wood Sci. and Forest Prod., Virginia Tech, Blacksburg, VA.

---------------, D.E. Kline, and P.A. Araman. 1992. Value of defect information in automated hardwood edger and trimmer systems. Forest Prod. J. 42(3):29-34.

Schumann, D.R. 1971. Dimension yields from black walnut lumber. USDA. Forest Service Research Paper FPL-162. Forest Products Laboratory, Madison, Wisc.

-------------------. 1972. Dimension Yields from alder. USDA. Forest Service Research Paper FPL-170. Forest Product Laboratory, Madison, Wisc.

Stern, A.R. and K.A. McDonald. 1978. Computer optimization of cutting yields from multi-ripped boards. USDA. Forest Service Research Paper FPL-318. Forest Products Laboratory, Madison Wisc.

-------------, and E.H. Bulgrin. 1978. An unpublished computer program. USDA. Forest Service. Forest Products Laboratory, Forest Products Laboratory, Madison, Wisc.

Szymani, R. and K.A. McDonald. 1981. Defect detection in lumber: state of the art. Forest Prod. J. 31(11):34-44.

Thomas, R.J. 1962. The rough-end Research Program. Forest Product Journal. 12(11):536-537

Thomas, R.E., C.J. Gatchell, and E.S. Walker. 1994. User's guide to AGARIS: advanced gang-rip simulator. Gen. Tech. Paper NE-192. Radnor, PA. USDA. Forest Service, Northeastern Forest Experiment Station. 54 p.

Thomas, R.E. 1995. ROMI-RIP: Rough mill rip-first simulator user's guide. Forest Products Laboratory General Technical Report NE-202, USDA Forest Service.

Wengert, E.M. and F.M. Lamb. 1994. A hand book for improving quality and efficiency in rough mill operations: Practical guideline, examples, and ideas. Virginia Polytechnic Institute and state University. Blacksburg, VA. pp. 12.

Wodzinski, C. and E. Hahn. 1966. A computer program to determine yields of lumber. USDA. Forest Service, Forest Products Laboratory, Madison, Wisc.

Yoo, S., C. J. Precetti, and D. Cassens. 1992. Color machine vision used to establish color grading standards for hardwood dimension parts. Presented at the 1992International Winter Meeting, Paper No. 923583. American Society of Agricultural Engineers. St. Joseph. Michigan.

Yun, L.Y. 1989. The margin for yield improvement for no.1 common 5/4 red oak in a conventional rough mill. Master's thesis, Virginia Polytechnic Institute and State University, 87 pp.

# APPENDICES

## Appendix 1

### Yield comparison on three methods (observed, optimum, scanned)

| No. | Board No. | Observed | | | Simulated | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Optimum | | | Scanned[1] | | |
| | | Primary | Salvage | Total | Primary | Salvage | Total | Primary | Salvage | Total |
| 1 | 167 | 58.02 | 0.00 | 58.02 | 59.81 | 0.00 | 59.81 | 46.83 | 0.00 | 46.83 |
| 2 | 187 | 74.20 | 0.00 | 74.20 | 77.44 | 0.00 | 77.44 | 34.78 | 9.17 | 43.95 |
| 3 | 149 | 43.53 | 9.12 | 52.65 | 80.16 | 0.00 | 80.16 | 37.40 | 0.00 | 37.40 |
| 4 | 139 | 71.58 | 0.00 | 71.58 | 82.06 | 2.64 | 84.70 | 63.37 | 0.00 | 63.37 |
| 5 | 133 | 32.26 | 8.21 | 40.47 | 52.44 | 0.00 | 52.44 | 51.63 | 3.56 | 55.19 |
| 6 | 141 | 58.41 | 5.31 | 63.72 | 71.01 | 0.00 | 71.01 | 40.09 | 4.30 | 44.39 |
| 7 | 163 | 70.84 | 0.00 | 70.84 | 77.34 | 2.49 | 79.83 | 52.85 | 2.49 | 55.34 |
| 8 | 179 | 80.96 | 0.00 | 80.96 | 79.73 | 0.00 | 79.73 | 60.48 | 0.00 | 60.48 |
| 9 | 161 | 53.44 | 2.66 | 56.10 | 69.01 | 3.85 | 72.86 | 41.35 | 0.00 | 41.35 |
| 10 | 172 | 67.20 | 0.00 | 67.20 | 71.32 | 0.00 | 71.32 | 56.54 | 0.00 | 56.54 |
| 11 | 155 | 53.15 | 0.00 | 53.15 | 59.09 | 5.67 | 64.76 | 37.83 | 0.00 | 37.83 |
| 12 | 124 | 74.59 | 0.00 | 74.59 | 77.69 | 0.00 | 77.69 | 57.38 | 0.00 | 57.38 |
| 13 | 129 | 52.03 | 13.10 | 65.13 | 67.72 | 4.60 | 72.32 | 60.16 | 0.00 | 60.16 |
| 14 | 160 | 60.30 | 4.03 | 64.33 | 65.46 | 10.33 | 75.79 | 52.39 | 0.00 | 52.39 |
| 15 | 150 | 41.09 | 12.92 | 54.01 | 53.33 | 0.00 | 53.33 | 43.64 | 0.00 | 43.64 |
| 16 | 136 | 59.35 | 0.00 | 59.35 | 68.44 | 0.00 | 68.44 | 37.68 | 8.11 | 45.79 |
| 17 | 168 | 80.12 | 0.00 | 80.12 | 82.20 | 0.00 | 82.20 | 56.38 | 0.00 | 56.38 |
| 18 | 142 | 58.76 | 0.00 | 58.76 | 64.45 | 0.00 | 64.45 | 28.54 | 0.00 | 28.54 |
| 19 | 154 | 70.30 | 0.00 | 70.30 | 73.07 | 0.00 | 73.07 | 58.52 | 0.00 | 58.52 |
| 20 | 146 | 47.38 | 11.05 | 58.43 | 59.88 | 8.06 | 67.94 | 39.16 | 0.00 | 39.16 |
| 21 | 144 | 38.49 | 17.77 | 56.26 | 65.45 | 0.00 | 65.45 | 48.48 | 0.00 | 48.48 |
| 22 | 177 | 68.54 | 3.19 | 71.73 | 74.60 | 1.18 | 75.78 | 55.65 | 0.00 | 55.65 |

[1] The scanned yield presented in Appendix 1 has not been adjusted for unacceptable defects undetected by the scanning system (false negative error). Appendix 3 makes this adjustment and shows how salvage yield and total yield for the scanned data are affected by false negative error.

| No. | Board No. | Observed | | | Simulated | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Optimum | | | Scanned[1] | | |
| | | Primary | Salvage | Total | Primary | Salvage | Total | Primary | Salvage | Total |
| 23 | 175 | 65.22 | 8.33 | 73.55 | 75.66 | 0.00 | 75.66 | 39.64 | 0.00 | 39.64 |
| 24 | 157 | 54.87 | 12.08 | 66.95 | 71.95 | 2.58 | 74.53 | 53.00 | 0.00 | 53.00 |
| 25 | 166 | 62.18 | 0.00 | 62.18 | 71.74 | 0.00 | 71.74 | 47.02 | 0.00 | 47.02 |
| 26 | 182 | 55.19 | 6.56 | 61.75 | 63.43 | 0.00 | 63.43 | 37.48 | 8.63 | 46.11 |
| 27 | 147 | 72.94 | 0.00 | 72.94 | 80.99 | 0.00 | 80.99 | 58.15 | 2.57 | 60.72 |
| 28 | 176 | 68.28 | 0.00 | 68.28 | 74.50 | 0.00 | 74.50 | 52.77 | 0.00 | 52.77 |
| 29 | 183 | 51.91 | 8.21 | 60.12 | 68.08 | 0.00 | 68.08 | 41.70 | 0.00 | 41.70 |
| 30 | 148 | 48.63 | 19.87 | 68.50 | 55.89 | 7.71 | 63.60 | 42.04 | 2.57 | 44.61 |
| 31 | 131 | 48.77 | 0.00 | 48.77 | 49.05 | 0.00 | 49.05 | 27.7 | 8.62 | 36.32 |
| 32 | 156 | 37.94 | 18.97 | 56.91 | 68.59 | 4.80 | 73.39 | 49.21 | 0.00 | 49.21 |
| 33 | 158 | 63.64 | 0.00 | 63.64 | 59.07 | 0.00 | 59.07 | 45.51 | 2.98 | 48.49 |
| 34 | 191 | 75.69 | 0.00 | 75.69 | 81.11 | 0.00 | 81.11 | 40.00 | 0.00 | 40.00 |
| 35 | 138 | 67.59 | 0.00 | 67.59 | 70.81 | 1.77 | 72.58 | 49.70 | 2.84 | 52.54 |
| 36 | 181 | 52.90 | 10.97 | 63.87 | 68.14 | 6.79 | 74.93 | 69.83 | 0.00 | 69.83 |
| 37 | 169 | 84.86 | 0.00 | 84.86 | 86.00 | 0.00 | 86.00 | 53.79 | 0.00 | 53.79 |
| 38 | 186 | 59.21 | 0.00 | 59.21 | 60.86 | 0.00 | 60.86 | 35.16 | 0.00 | 35.16 |
| 39 | 188 | 64.21 | 6.83 | 71.04 | 71.90 | 6.66 | 78.56 | 54.35 | 0.00 | 54.35 |
| 40 | 174 | 46.70 | 8.80 | 55.50 | 65.45 | 0.00 | 65.45 | 52.29 | 0.00 | 52.29 |
| 41 | 185 | 63.91 | 3.61 | 67.52 | 68.56 | 0.00 | 68.56 | 51.56 | 0.00 | 51.56 |
| 42 | 137 | 43.68 | 10.99 | 54.67 | 60.01 | 0.00 | 60.01 | 31.67 | 0.00 | 31.67 |
| 43 | 122 | 46.65 | 14.00 | 60.65 | 59.74 | 2.46 | 62.20 | 50.27 | 0.00 | 50.27 |
| 44 | 123 | 67.37 | 0.00 | 67.37 | 67.72 | 2.14 | 69.86 | 51.73 | 2.14 | 53.87 |
| 45 | 170 | 68.45 | 4.41 | 72.86 | 70.77 | 0.00 | 70.77 | 47.18 | 0.00 | 47.18 |
| 46 | 171 | 62.30 | 0.00 | 62.30 | 66.50 | 3.79 | 70.29 | 26.53 | 0.00 | 26.53 |
| 47 | 159 | 70.04 | 0.00 | 70.04 | 74.54 | 0.00 | 74.54 | 62.06 | 4.11 | 66.17 |
| 48 | 178 | 59.06 | 0.00 | 59.06 | 59.03 | 0.00 | 59.03 | 28.04 | 0.00 | 28.04 |
| 49 | 128 | 67.42 | 0.00 | 67.42 | 75.99 | 0.00 | 75.99 | 66.83 | 0.00 | 66.83 |
| 50 | 162 | 58.65 | 0.00 | 58.65 | 52.95 | 8.34 | 61.29 | 41.22 | 4.11 | 45.33 |
| 51 | 173 | 67.46 | 3.94 | 71.40 | 71.77 | 1.71 | 73.48 | 59.38 | 0.00 | 59.38 |
| 52 | 135 | 64.33 | 0.00 | 64.33 | 58.82 | 0.00 | 58.82 | 29.67 | 5.68 | 35.35 |
| 53 | 126 | 57.96 | 6.42 | 64.38 | 75.46 | 0.00 | 75.46 | 64.41 | 0.00 | 64.41 |
| 54 | 140 | 58.84 | 3.03 | 61.87 | 69.23 | 0.00 | 69.23 | 51.05 | 0.00 | 51.05 |
| 55 | 190 | 48.17 | 3.46 | 51.63 | 65.51 | 0.00 | 65.51 | 53.09 | 6.42 | 59.51 |
| 56 | 145 | 61.02 | 7.19 | 68.21 | 68.21 | 0.00 | 68.21 | 57.58 | 0.00 | 57.58 |
| 57 | 130 | 58.98 | 4.21 | 63.19 | 64.34 | 8.22 | 72.56 | 49.64 | 0.00 | 49.64 |
| 58 | 152 | 70.23 | 0.00 | 70.23 | 79.78 | 0.00 | 79.78 | 62.43 | 2.76 | 65.19 |

| No. | Board No. | Observed | | | Simulated | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Optimum | | | Scanned[1] | | |
| | | Primary | Salvage | Total | Primary | Salvage | Total | Primary | Salvage | Total |
| 59 | 132 | 64.72 | 5.25 | 69.97 | 65.87 | 3.54 | 69.41 | 56.02 | 0.00 | 56.02 |
| 60 | 143 | 54.12 | 8.03 | 62.15 | 68.74 | 0.00 | 68.74 | 39.89 | 3.67 | 43.56 |
| 61 | 189 | 56.14 | 11.02 | 67.16 | 85.76 | 0.00 | 85.76 | 61.08 | 2.58 | 63.66 |
| 62 | 151 | 64.75 | 0.00 | 64.75 | 74.16 | 0.00 | 74.16 | 59.68 | 0.00 | 59.68 |
| 63 | 127 | 46.77 | 19.77 | 66.54 | 66.64 | 2.31 | 68.95 | 53.56 | 0.00 | 53.56 |
| 64 | 134 | 63.85 | 0.00 | 63.85 | 81.02 | 0.00 | 81.02 | 49.29 | 0.00 | 49.29 |
| 65 | 125 | 54.55 | 0.00 | 54.55 | 71.07 | 0.00 | 71.07 | 53.72 | 0.00 | 53.72 |
| 66 | 165 | 65.27 | 0.00 | 65.27 | 70.04 | 0.00 | 70.04 | 64.05 | 0.00 | 64.05 |
| 67 | 184 | 62.48 | 2.32 | 64.80 | 61.66 | 4.82 | 66.48 | 40.19 | 2.35 | 42.54 |
| 68 | 24 | 64.31 | 0.00 | 64.31 | 78.82 | 0.00 | 78.82 | 45.63 | 0.00 | 45.63 |
| 69 | 153 | 73.86 | 0.00 | 73.86 | 78.44 | 0.00 | 78.44 | 44.00 | 0.00 | 44.00 |
| 70 | 72 | 53.02 | 3.21 | 56.23 | 65.40 | 0.00 | 65.40 | 33.60 | 7.00 | 40.60 |
| 71 | 114 | 69.91 | 2.16 | 72.07 | 69.86 | 3.13 | 72.99 | 46.38 | 0.00 | 46.38 |
| 72 | 112 | 57.28 | 3.01 | 60.29 | 62.08 | 2.75 | 64.83 | 44.81 | 7.79 | 52.6 |
| 73 | 119 | 57.38 | 0.00 | 57.38 | 51.95 | 2.14 | 54.09 | 48.66 | 0.00 | 48.66 |
| 74 | 77 | 62.18 | 2.41 | 64.59 | 69.88 | 1.72 | 71.60 | 48.29 | 6.93 | 55.22 |
| 75 | 30 | 55.92 | 9.05 | 64.97 | 50.40 | 13.68 | 64.08 | 49.59 | 0.00 | 49.59 |
| 76 | 25 | 66.52 | 0.00 | 66.52 | 71.39 | 0.00 | 71.39 | 59.42 | 0.00 | 59.42 |
| 77 | 121 | 54.41 | 0.00 | 54.41 | 59.69 | 0.00 | 59.69 | 36.07 | 0.00 | 36.07 |
| 78 | 42 | 31.82 | 11.55 | 43.37 | 48.06 | 0.00 | 48.06 | 31.78 | 3.29 | 35.07 |
| 79 | 164 | 53.89 | 2.96 | 56.85 | 57.12 | 0.00 | 57.12 | 47.73 | 0.00 | 47.73 |
| 80 | 26 | 41.97 | 15.92 | 57.89 | 68.49 | 6.71 | 75.20 | 44.54 | 0.00 | 44.54 |
| 81 | 71 | 60.93 | 9.31 | 70.24 | 66.45 | 3.43 | 69.88 | 45.53 | 6.17 | 51.70 |
| 82 | 40 | 65.71 | 0.00 | 65.71 | 71.04 | 2.33 | 73.37 | 54.42 | 2.92 | 57.34 |
| 83 | 29 | 72.25 | 0.00 | 72.25 | 75.58 | 5.70 | 81.28 | 53.17 | 4.38 | 57.55 |
| 84 | 16 | 49.91 | 15.86 | 65.77 | 61.66 | 2.19 | 63.85 | 33.99 | 0.00 | 33.99 |
| 85 | 64 | 65.79 | 3.13 | 68.92 | 71.55 | 4.10 | 75.65 | 50.64 | 0.00 | 50.64 |
| 86 | 17 | 57.84 | 0.00 | 57.84 | 59.43 | 4.97 | 64.40 | 54.51 | 0.00 | 54.51 |
| 87 | 13 | 53.64 | 10.73 | 64.37 | 53.39 | 0.00 | 53.39 | 40.53 | 0.00 | 40.53 |
| 88 | 108 | 53.86 | 0.00 | 53.86 | 69.46 | 0.00 | 69.46 | 46.67 | 0.00 | 46.67 |
| 89 | 100 | 68.98 | 0.00 | 68.98 | 64.80 | 0.00 | 64.80 | 51.20 | 0.00 | 51.20 |
| 90 | 74 | 72.50 | 0.00 | 72.50 | 74.98 | 0.00 | 74.98 | 33.23 | 0.00 | 33.23 |
| 91 | 87 | 68.40 | 2.60 | 71.00 | 75.07 | 0.00 | 75.07 | 61.27 | 0.00 | 61.27 |
| 92 | 18 | 59.71 | 0.00 | 59.71 | 68.62 | 0.00 | 68.62 | 52.75 | 0.00 | 52.75 |
| 93 | 115 | 52.41 | 2.29 | 54.70 | 59.15 | 5.57 | 64.72 | 47.01 | 3.51 | 50.52 |
| 94 | 68 | 61.42 | 0.00 | 61.42 | 72.81 | 1.66 | 74.47 | 42.42 | 0.00 | 42.42 |

| No. | Board No. | Observed | | | Simulated | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Optimum | | | Scanned[1] | | |
| | | Primary | Salvage | Total | Primary | Salvage | Total | Primary | Salvage | Total |
| 95 | 14 | 63.17 | 0.00 | 63.17 | 58.30 | 0.00 | 58.30 | 20.38 | 15.67 | 36.05 |
| 96 | 116 | 45.11 | 7.89 | 53.00 | 68.99 | 5.66 | 74.65 | 41.81 | 0.00 | 41.81 |
| 97 | 46 | 61.10 | 2.97 | 64.07 | 59.72 | 2.45 | 62.17 | 52.63 | 3.52 | 56.15 |
| 98 | 106 | 63.34 | 0.00 | 63.34 | 55.84 | 5.78 | 61.62 | 43.03 | 0.00 | 43.03 |
| 99 | 96 | 67.06 | 2.84 | 69.90 | 69.08 | 5.60 | 74.68 | 68.41 | 0.00 | 68.41 |
| 100 | 32 | 78.95 | 0.00 | 78.95 | 87.37 | 0.00 | 87.37 | 68.11 | 0.00 | 68.11 |
| 101 | 120 | 67.17 | 0.00 | 67.17 | 63.44 | 0.00 | 63.44 | 35.29 | 14.28 | 49.57 |
| 102 | 9 | 72.90 | 0.00 | 72.90 | 75.51 | 0.00 | 75.51 | 65.92 | 0.00 | 65.92 |
| 103 | 3 | 77.25 | 0.00 | 77.25 | 78.55 | 0.00 | 78.55 | 72.23 | 0.00 | 72.23 |
| 104 | 10 | 67.73 | 2.80 | 70.53 | 75.07 | 0.00 | 75.07 | 46.3 | 1.94 | 48.24 |
| 105 | 99 | 43.15 | 11.21 | 54.36 | 67.75 | 0.00 | 67.75 | 41.76 | 0.00 | 41.76 |
| 106 | 73 | 66.04 | 0.00 | 66.04 | 79.93 | 0.00 | 79.93 | 52.35 | 0.00 | 52.35 |
| 107 | 82 | 79.46 | 0.00 | 79.46 | 80.73 | 0.00 | 80.73 | 50.65 | 3.53 | 54.18 |
| 108 | 8 | 70.12 | 0.00 | 70.12 | 70.78 | 0.00 | 70.78 | 46.29 | 0.00 | 46.29 |
| 109 | 12 | 49.36 | 2.97 | 52.33 | 64.15 | 1.72 | 65.87 | 52.38 | 2.75 | 55.13 |
| 110 | 113 | 55.93 | 11.09 | 67.02 | 65.26 | 5.33 | 70.59 | 49.36 | 0.00 | 49.36 |
| 111 | 90 | 72.31 | 2.89 | 75.20 | 65.74 | 0.00 | 65.74 | 57.13 | 2.68 | 59.81 |
| 112 | 15 | 37.03 | 11.29 | 48.32 | 59.18 | 0.00 | 59.18 | 47.63 | 3.85 | 51.48 |
| 113 | 93 | 68.51 | 2.70 | 71.21 | 66.86 | 0.00 | 66.86 | 37.03 | 0.00 | 37.03 |
| 114 | 81 | 58.76 | 3.09 | 61.85 | 67.24 | 2.56 | 69.80 | 39.65 | 0.00 | 39.65 |
| 115 | 33 | 72.98 | 4.11 | 77.09 | 73.14 | 1.78 | 74.92 | 44.85 | 5.80 | 50.65 |
| 116 | 107 | 63.77 | 0.00 | 63.77 | 79.22 | 0.00 | 79.22 | 47.76 | 0.00 | 47.76 |
| 117 | 98 | 66.13 | 0.00 | 66.13 | 73.26 | 0.00 | 73.26 | 46.89 | 0.00 | 46.89 |
| 118 | 92 | 71.40 | 0.00 | 71.40 | 79.46 | 2.54 | 82.00 | 54.57 | 0.00 | 54.57 |
| 119 | 6 | 57.03 | 0.00 | 57.03 | 69.68 | 2.37 | 72.05 | 46.05 | 5.31 | 51.36 |
| 120 | 111 | 75.58 | 0.00 | 75.58 | 70.62 | 1.78 | 72.40 | 55.81 | 0.00 | 55.81 |
| 121 | 109 | 74.72 | 0.00 | 74.72 | 65.58 | 0.00 | 65.58 | 46.82 | 0.00 | 46.82 |
| 122 | 105 | 70.28 | 0.00 | 70.28 | 71.05 | 2.03 | 73.08 | 38.27 | 0.00 | 38.27 |
| 123 | 101 | 66.18 | 0.00 | 66.18 | 72.42 | 1.78 | 74.20 | 42.4 | 0.00 | 42.4 |
| 124 | 85 | 59.80 | 0.00 | 59.80 | 63.10 | 6.90 | 70.00 | 40.09 | 0.00 | 40.09 |
| 125 | 91 | 80.62 | 0.00 | 80.62 | 81.48 | 0.00 | 81.48 | 59.86 | 1.67 | 61.53 |
| 126 | 94 | 71.29 | 0.00 | 71.29 | 75.55 | 0.00 | 75.55 | 51.69 | 2.67 | 54.36 |
| 127 | 60 | 41.64 | 5.07 | 46.71 | 57.81 | 0.00 | 57.81 | 45.39 | 0.00 | 45.39 |
| 128 | 70 | 72.44 | 3.98 | 76.42 | 78.56 | 0.00 | 78.56 | 54.03 | 0.00 | 54.03 |
| 129 | 110 | 63.71 | 2.59 | 66.30 | 67.73 | 2.65 | 70.38 | 56.64 | 0.00 | 56.64 |
| 130 | 104 | 52.41 | 2.07 | 54.48 | 59.03 | 0.00 | 59.03 | 37.72 | 0.00 | 37.72 |

| No. | Board No. | Observed | | | Simulated | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Optimum | | | Scanned[1] | | |
| | | Primary | Salvage | Total | Primary | Salvage | Total | Primary | Salvage | Total |
| 131 | 5 | 51.12 | 11.66 | 62.78 | 71.69 | 0.00 | 71.69 | 44.92 | 9.79 | 54.71 |
| 132 | 61 | 70.38 | 2.79 | 73.17 | 73.92 | 0.00 | 73.92 | 45.74 | 5.79 | 51.53 |
| 133 | 97 | 66.91 | 1.76 | 68.67 | 48.84 | 16.85 | 65.69 | 48.99 | 9.48 | 58.47 |
| 134 | 49 | 36.63 | 10.65 | 47.28 | 57.73 | 6.69 | 64.42 | 38.34 | 0.00 | 38.34 |
| **Total Yield:** | | **62.20** | **3.40** | **65.60** | **67.40** | **1.72** | **69.10** | **49.35** | **1.62** | **50.97** |

**Appendix 2**

**Cuttings produced from the observed mill that require additional rework due to unacceptable defects**

| Part No. | Dimension | Description of Rejection (defect left larger than 0.0625 sq.in.) | Cutting Operation Needed | Salvage |
|---|---|---|---|---|
| 62 A2 | 2.5 x 34.5 | Unsound knot | Re-chop | 2.5 x 30 |
| 56 A2 | 2.5 x 16 | Unsound knot + bark pocket | Re-chop | 2.5 x 10 |
| 54 A3 | 2.5 x 16 | Unsound knot | Re-chop | 2.5 x 10 |
| 54 B3 | 1.75 x 20.5 | Wane | Re-chop | 1.75 x 10 |
| 33 A1 | 2.5 x 16 | Wane | Re-chop | 2.5 x 10 |
| 21 A5 | 3 x 16 | Unsound knot | Re-chop | 3 x 10 |
| 142 A1 | 2.5 x 16 | Grub hole | Re-rip | 1.75 x 16 |
| 139 A2 | 1.75 x 16 | Not fit to the size (width) | Re-chop | 1.75 x 10 |
| 23 B1 | 3 x 26.5 | Unsound knot | Re-chop | 3 x 16 |
| 22 C1 | 2.5 x 16 | Unsound knot | Re-chop | 2.5 x 10 |
| 103 A3 | 3 x 16 | Unsound knot | Re-chop | 3 x 10 |
| 54 A1 | 2.5 x 16 | Split | Re-chop | 2.5 x 10 |
| 79 B1 | 1.75 x 58.5 | Split | Re-chop | 1.75 x 50 |
| 37 B2 | 1.75 x 50 | Split | Re-chop | 1.75x32.5 |
| 102 A4 | 2.5 x 34.5 | Split + unsound knot | Re-chop | 2.5 x 26.5 |
| 64 B4 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 75 B3 | 2.5 x 16 | Unsound knot | Re-chop | 2.5 x 10 |
| 81 A1 | 3 x 44.5 | Unsound knot | Re-chop | 3 x 30 |
| | | | | 3 x 10 |
| 81 A3 | 3 x 44.5 | Unsound knot | Re-chop | 3 x 30 |
| | | | | 3 x 10 |
| 90 A5 | 2.5 x 26.5 | Unsound knot + bark pocket | Re-chop | 2.5 x 16 |
| 90 A6 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 123 A1 | 3 x 16 | Unsound knot | Re-chop | 3 x 10 |
| 141 A1 | 3 x 44.5 | Unsound knot | Re-chop | 3 x 30 |
| | | | | 3 x 10 |
| 138 A5 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 120 A4 | 3 x 16 | Split | Re-chop | 3 x 10 |

| Part No. | Dimension | Description of Rejection (defect left larger than 0.0625 sq.in.) | Cutting Operation Needed | Salvage |
|---|---|---|---|---|
| 85 A3 | 1.75 x 16 | Wane | Re-chop | 1.75 x 10 |
| 82 A2 | 3 x 16 | Grub hole | Re-chop | 3 x 10 |
| 121 A2 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 22 A4 | 2.5 x 16 | Not fit to the size (width) | Re-chop | 2.5 x 10 |
| 110 D6 | 2.5 x 16 | Split | Re-chop | 2.5 x 10 |
| 121A4 | 2.5 x 16 | Not fit to the size (width) | Re- chop | 2.5 x 16 |
| 139A2 | 1.75 x 16 | Not fit to the siza (width) | Re-chop | 1.75 x 10 |
| 143 B3 | 2.5 x 16 | Wane | Re-chop | 2.5 x 10 |
| 144 A6 | 3 x 10 | Wane | Re-rip | 2.5 x 10 |
| 136 A5 | 3 x 10 | Unsound knot | Re-rip | 1.75 x 10 |
| 144 A3 | 3 x 16 | Split | Re-rip | 2.5 x 16 |
| 138 A1<br>142 A1 | 2.5 x 16<br>3 x 16 | Not fit to the size (width)<br>Grub hole | Re-rip<br>Re-rip | 1.75 x 16<br>2.5 x 16 |
| 111 A3 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 94 B4 | 2.5 x 16 | Unsound knot | Re-chop | 2.5 x 10 |
| 111 A2 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 144A5 | 3 x 16 | Wane | Re-rip | 1.75 x 16 |
| 144A4 | 3 x 16 | Wane | Re-rip | 1.75 x 16 |
| 124 A3 | 3 x 16 | Split | Re-rip | 1.75 x 16 |
| 98 B3 | 2.5 x 16 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 82 B2 | 3 x 10 | Grub hole | Re-rip | 2.5 x 10 |
| 82 B1 | 3 x 16 | Not fit to the size (width) | Re-rip | 2.5 x 16 |
| 105 A1 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 137 A5 | 3 x 16 | Split | Re-rip | 2.5 x 16 |
| 114 A5 | 2.5 x 16 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 88 A4 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 122 A1 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 86 B1 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 119 A1 | 3 x 16 | Wane and not fit to the size (width) | Re-rip and re-chop | 2.5 x 10 |
| 98 B2 | 2.5 x 16 | Wane and split | Re-rip and re-chop | 1.75 x 10 |
| 73 B5 | 2.5 x 16 | Unsound knot | Re-rip | 1.75 x 16 |
| 111 A6 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 71 A1 | 2.5 x 16 | Split | Re-chop | 2.5 x 10 |

| Part No. | Dimension | Description of Rejection (defect left larger than 0.0625 sq.in.) | Cutting Operation Needed | Salvage |
|---|---|---|---|---|
| 105 A2 | 2.5 x 13 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 119 A2 | 3 x 16 | Wane | Re-rip | 2.5 x 16 |
| 111 A5 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 98 B1 | 2.5 x 16 | Wane | Re-chop | 2.5 x 10 |
| 111 A7 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 86 A4 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 111 A1 | 2.5 x 16 | Not fit to the size (width) | Re-rip and re-chop | 1.75 x 10 |
| 76 A5 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 90 A1 | 2.5 x 16 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 110 C1 | 2.5 x 16 | Split | Re-rip | 1.75 x 16 |
| 72 A2 | 2.5 x 13 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 121 A1 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 64 A1 | 3 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 64 A2 | 3 x 16 | Unsound knot | Re-chop | 3 x 10 |
| 96 A5 | 3 x 11 | Decay | Re-rip and re-chop | 1.75 x 10 |
| 96 A4 | 3 x 13 | Unsound knot | Re-chop | 3 x 10 |
| 117 A5 | 3 x 13 | Unsound knot | Re-chop | 3 x 10 |
| 61 A1 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 68 B4 | 1.75 x 16 | Unsound knot | Re-chop | 1.75 x 10 |
| 61 A5 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 64 B3 | 2.5 x 16 | Unsound knot | Re-chop | 2.5 x 10 |
| 119 A5 | 3 x 16 | Not fit to the size (width) | Re-rip | 2.5 x 16 |
| 64 A5 | 3 x 16 | Not fit to the size (width) | Re-rip | 2.5 x 16 |
| 55 A1 | 1.75 x 16 | Wane | Re-chop | 1.75 x 10 |
| 58 A3 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 44 B3 | 2.5 x 13 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 57 B3 | 2.5 x 16 | Wane | Re-chop | 2.5 x 10 |
| 33A3 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 39 A4 | 1.75 x 16 | Wane | Re-chop | 1.75 x 10 |
| 43 A2 | 3 x 16 | Wane | Re-rip | 2.5 x 16 |
| 46 A1 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |

| Part No. | Dimension | Description of Rejection (defect left larger than 0.0625 sq.in.) | Cutting Operation Needed | Salvage |
|---|---|---|---|---|
| 25 A3 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 44 A2 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 27 A2 | 1.75 x 16 | Wane | Re-chop | 1.75 x 10 |
| 41 A5 | 2.5 x 16 | Not fit to the size (width) | Re-rip and re-chop | 1.75 x 10 |
| 25 A2 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 43 A3 | 3 x 10 | Wane | Re-rip | 1.75 x 10 |
| 44 A3 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 44 B1 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 31 B1 | 3 x 16 | Not fit to the size (width) | Re-rip | 2.5 x 16 |
| 44 A5 | 2.5 x 16 | Not fit to the size (width) | Re-chop | 2.5 x 10 |
| 31 A1 | 3 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 57 A6 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 31 A2 | 2.5 x 16 | Not fit to the size (width) | Re-rip and re-chop | 1.75 x 10 |
| 52 A1 | 3 x 16 | Wane | Re-rip | 2.5 x 16 |
| 31 B2 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 31 A3 | 3 x 16 | Not fit to the size (width) | Re-rip | 2.5 x 16 |
| 40 A6 | 3 x 16 | Wane and split | Re-rip | 1.75 x 16 |
| 22 C5 | 2.5 x 10 | Wane | Re-rip | 1.75 x 10 |
| 21 B5 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 21 A6 | 3 x 16 | Wane and unsound knot | Re-rip and re-chop | 2.5 x 10 |
| 22 C4 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 22 C2 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 36 C1 | 2.5 x 16 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 25 A1 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 22A5 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 13 B5 | 2.5 x 16 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 22 C3 | 2.5 x 16 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 16 A5 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 33 A4 | 2.5 x 13 | Wane | Re-rip and re-chop | 1.75 x 10 |
| 4 A4 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |

| Part No. | Dimension | Description of Rejection (defect left larger than 0.0625 sq.in.) | Cutting Operation Needed | Salvage |
|---|---|---|---|---|
| 42 B4 | 2.5 x 16 | Unsound knot | Re-chop | 2.5 x 10 |
| 40 B1 | 2.5 x 16 | Wane | Re-rip | 1.75 x 16 |
| 30 A3 | 3 x 16 | Wane | Re-rip | 2.5 x 16 |
| 14 B3 | 2.5 x 16 | Wane | Re-chop | 1.75 x 16 |
| 65 A1 | 3 x 16 | Not fit to the size (width) | Re-rip | 2.5 x 16 |
| 16 A4 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 24 A5 | 3 x 16 | Wane | Re-chop | 3 x 10 |
| 10 A2 | 2.5 x 16 | Wane and unsound knot | Re-rip and re-chop | 1.75 x 10 |
| 15 A1 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 97 A4 | 2.5 x 16 | Split | Re-rip and re-chop | 1.75 x 10 |
| 16A1 | 2.5 x 16 | Not fit to the size (width) | Re-rip and re-chop | 1.75 x 10 |
| 97 D4 | 2.5 x 13 | Split | Re-rip and re-chop | 1.75 x 10 |
| 5 A4 | 3 x 16 | Split | Re-rip | 1.75 x 16 |
| 1 A4 | 1.75 x 16 | Wane | Re-chop | 1.75 x 10 |
| 3 A3 | 2.5 x 16 | Split | Re-rip | 1.75 x 16 |
| 4 A5 | 2.5 x 16 | Not fit to the size (width) | Re-rip | 1.75 x 16 |
| 60 B3 | 1.75 x 32.5 | Split | Re-chop | 1.75 x 30 |
| 14 A5 | 3 x 30 | Wane | Re-rip | 2.5 x 30 |
| 24 A5 | 2.5 x 30 | Wane | Re-rip | 1.75 x 30 |
| 96 A1 | 3 x 26.5 | Unsound knot | Re-chop | 3 x 16 |
| 41 A2 | 1.75 x 30 | Wane | Re-chop | 1.75 x 10 |
| 76 B2 | 2.5 x 30 | Wane | Re-rip | 1.75 x 30 |
| 27 A2 | 1.75 x 30 | Wane | Re-chop | 1.75 x 10 |
| 7 B1 | 1.75 x 30 | Wane | Re-chop | 1.75 x 10 |
| | Total volume (BF): 45.23 | | | Total volume (BF): 30.52 |

**Appendix 3**

**Cuttings produced from the scanned data that require additional rework due to unacceptable defects**

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| 139 | 2 | 16 x 2.5 | 40 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| 133 | 1 | 30 x 3 | 90 | 2 | Void | No | P | 26.5 x 3 | 79.5 |
| 133 | 3 | 44.5 x 3 | 133.5 | 8 | Wane | No | P | 30 x 3 | 90 |
| | | | 0 | | | | | 10 x 1.75 | 17.5 |
| 179 | 10 | 20.5 x 1.75 | 35.875 | 10 | Bark pockert | No | P | 16 x 1.75 | 28 |
| 179 | 12 | 50 x 1.75 | 87.5 | 10 | Bark pockert | No | P | 20.5x1.75 | 35.875 |
| | | | | | | | | 16 x 1.75 | 28 |
| 172 | 3 | 26.5 x 2.5 | 66.25 | 24 | Split | No | P | 16 x 2.5 | 40 |
| 172 | 4 | 16 x 2.5 | 40 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| 155 | 2 | 32.5 x 1.75 | 56.875 | 12 | Unsound knot | No | P | 30 x 1.75 | 52.5 |
| 124 | 3 | 16 x 2.5 | 40 | 24 | Split | No | P | 16 x 2.5 | 40 |
| 129 | 3 | 58.5 x 1.75 | 102.375 | 24 | Split | No | P | 50 x 1.75 | 87.5 |
| 136 | 1 | 44.5 x 3 | 133.5 | 24 | Split | No | P | 26.5 x 3 | 79.5 |
| | | | | | | | | 16 x 3 | 48 |
| 136 | 4 | 10 x 1.75 | 17.5 | 5 | Shake | No | S | | 0 |
| 142 | 1 | 32.5 x 1.75 | 56.875 | 12 | Unsound knot | No | P | 30 x 1.75 | 52.5 |
| 148 | 4 | 32.5 x 1.75 | 56.875 | 2 | Void | No | P | 10 x 1.75 | 17.5 |
| 131 | 2 | 16 x 2.5 | 40 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| 131 | 3 | 26.5 x 2.5 | 66.25 | 8 | Wane | No | P | 16 x 2.5 | 40 |
| | | | | | | | | 10 x 1.75 | 17.5 |
| 131 | 5 | 10 x 1.75 | 17.5 | 10 | Bark pockert | No | S | | 0 |
| 181 | 1 | 58.5 x 2.5 | 146.25 | 24 | Split | No | P | 55.5 x 2.5 | 138.75 |

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| 181 | 4 | 58.5 x 1.75 | 102.375 | 8 | Wane | No | P | 50 x 1.75 | 87.5 |
| 181 | 6 | 20.5 x 1.75 | 35.875 | 24 | Split | No | P | 10 x 1.75 | 17.5 |
| 186 | 1 | 10 x 2.5 | 25 | 14 | Surface check | No | P | 10 x 1.75 | 17.5 |
| 188 | 4 | 58.5 x 2.5 | 146.25 | 24 | Split | No | P | 55.5 x 2.5 | 138.75 |
| 185 | 1 | 58.5 x 2.5 | 146.25 | 24 | Split | No | P | 55.5 x 2.5 | 138.75 |
| 123 | 5 | 55.5 x 2.5 | 138.75 | 15 | Sound knot | Yes | P | 55.5 x 2.5 | 138.75 |
| 170 | 1 | 44.5 x 3 | 133.5 | 24 | Split | No | P | 26.5 x 3 | 79.5 |
| | | | | | | | | 16 x 3 | 48 |
| 159 | 1 | 30 x 1.75 | 52.5 | 24 | Split | No | P | 20.5x1.75 | 35.875 |
| 128 | 6 | 50 x 1.75 | 87.5 | 8 | Wane | No | P | 32.5x1.75 | 56.875 |
| 162 | 1 | 58.5 x 1.75 | 102.375 | 24 | Split | No | P | 50 x 1.75 | 87.5 |
| 126 | 6 | 16 x 1.75 | 28 | 12 | Unsound knot | No | P | 10 x 1.75 | 17.5 |
| 190 | 3 | 34.5 x 2.5 | 86.25 | 10 | Bark pockert | No | P | 16 x 2.5 | 40 |
| | | | | | | | | 16 x 2.5 | 40 |
| 190 | 4 | 10 x 2.5 | 25 | 24 | Split | No | P | 10 x 1.75 | 17.5 |
| 132 | 2 | 26.5 x 3 | 79.5 | 24 | Split | No | P | 16 x 3 | 48 |
| | | | | | | | | 10 x 1.75 | 17.5 |
| 132 | 3 | 16 x 3 | 48 | 24 | Split | No | P | 10 x 1.75 | 17.5 |
| 132 | 4 | 58.5 x 2.5 | 146.25 | 9 | | No | P | 58.5 x 2.5 | 146.25 |
| 189 | 5 | 32.5 x 1.75 | 56.875 | 12 | Unsound knot | No | P | 20.5x1.75 | 35.875 |
| 189 | 7 | 10 x 1.75 | 17.5 | 12 | Unsound knot | No | S | | 0 |
| 151 | 1 | 30 x 2.5 | 75 | 15 | Sound knot | Yes | P | 26.5 x 2.5 | 66.25 |
| 127 | 1 | 55.5 x 2.5 | 138.75 | 24 | Split | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 16 x 2.5 | 40 |
| 127 | 4 | 20.5 x 1.75 | 35.875 | 2 | Void | No | P | 16 x 1.75 | 28 |
| 125 | 6 | 58.5 x 2.5 | 146.25 | 12 | Unsound knot | No | P | 55.5 x 2.5 | 138.75 |
| 184 | 4 | 10 x 2.5 | 25 | 24 | Split | No | P | 10 x 1.75 | 17.5 |
| 184 | 5 | 55.5 x 2.5 | 138.75 | 12 | Unsound knot | No | P | 55.5 x 2.5 | 138.75 |
| 184 | 6 | 10 x 2.5 | 25 | 12 | Unsound knot | No | P | 10 x 1.75 | 17.5 |
| 24 | 2 | 32.5 x 1.75 | 56.875 | 10 | Bark | No | P | 10 x 1.75 | 17.5 |

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | pockert | | | | |
| | | | | | | | | 10 x 1.75 | 17.5 |
| 72 | 5 | 16 x 2.5 | 40 | 24 | Split | No | P | 10 x 2.5 | 25 |
| 114 | 1 | 44.5 x 3 | 133.5 | 24 | Split | No | P | 44.5 x 3 | 133.5 |
| 114 | 4 | 26.5 x 3 | 79.5 | 10 | Bark pockert | No | P | 26.5 x 3 | 79.5 |
| 112 | 3 | 26.5 x 2.5 | 66.25 | 12 | Unsound knot | No | P | 16 x 2.5 | 40 |
| | | | | | | | | 10 x 1.75 | 17.5 |
| 112 | 4 | 55.5 x 2.5 | 138.75 | 10 | Bark pockert | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 16 x 2.5 | 40 |
| 112 | 7 | 20.5 x 1.75 | 35.875 | 10 | Bark pockert | No | S | 10 x 1.75 | 17.5 |
| 112 | 8 | 10 x 1.75 | 17.5 | 10 | Bark pockert | No | S | | 0 |
| 119 | 2 | 32.5 x 1.75 | 56.875 | 10 | Bark pockert | No | P | 20.5x1.75 | 35.875 |
| | | | | | | | | 10 x 1.75 | 17.5 |
| 119 | 3 | 10 x 1.75 | 17.5 | 24 | Split | No | P | | 0 |
| 119 | 5 | 58.5 x 2.5 | 146.25 | 12 | Unsound knot | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 16 x 2.5 | 40 |
| 25 | 5 | 58.5 x 2.5 | 146.25 | 10 | Bark pockert | No | P | 58.5x1.75 | 102.375 |
| 42 | 2 | 16 x 3 | 48 | 12 | Unsound knot | No | P | 16 x 2.5 | 40 |
| 42 | 4 | 10 x 3 | 30 | 10 | Bark pockert | No | P | 10 x 2.5 | 25 |
| 164 | 1 | 55.5 x 2.5 | 138.75 | 24 | Split | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 16 x 2.5 | 40 |
| 26 | 2 | 58.5 x 2.5 | 146.25 | 8 | Wane | No | P | 58.5x1.75 | 102.375 |
| 71 | 5 | 55.5 x 2.5 | 138.75 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| | | | | | | | | 34.5 x 2.5 | 86.25 |
| 40 | 1 | 16 x 2.5 | 40 | 24 | Split | No | P | 10 x 2.5 | 25 |
| 16 | 2 | 44.5 x 3 | 133.5 | 15 | Sound knot | Yes | P | 34.5 x 2.5 | 86.25 |

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | and Unsound knot | No | | | |
| | | | | | | | | 10 x 2.5 | 25 |
| 17 | 2 | 55.5 x 2.5 | 138.75 | 10 | Bark pockert | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 16 x 2.5 | 40 |
| 17 | 4 | 16 x 2.5 | 40 | 10 | Bark pockert | No | P | 10 x 2.5 | 25 |
| 17 | 5 | 10 x 2.5 | 25 | 10 | Bark pockert | No | P | 10 x 2.5 | 25 |
| 17 | 6 | 16 x 2.5 | 40 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| 17 | 7 | 16 x 2.5 | 40 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| 17 | 8 | 55.5 x 2.5 | 138.75 | 10 | Bark pockert | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 16 x 2.5 | 40 |
| 17 | 9 | 10 x 2 | 20 | 10 | Bark pockert | No | S | | 0 |
| 17 | 10 | 10 x 1.75 | 17.5 | 12 | Unsound knot | No | S | | 0 |
| 13 | 6 | 10 x 1.75 | 17.5 | 12 | Unsound knot | No | S | | 0 |
| 108 | 1 | 58.5 x 1.75 | 102.375 | 8 | Wane | No | P | 32.5x1.75 | 56.875 |
| | | | | | | | | 16 x 1.75 | 28 |
| 108 | 5 | 20.5 x 1.75 | 35.875 | 10 | Bark pockert | No | P | 16 x 1.75 | 28 |
| 100 | 4 | 16 x 2.5 | 40 | 16 | Machining defect | No | P | 10 x 2.5 | 25 |
| 87 | 5 | 34.5 x 2.5 | 86.25 | 8 | Wane | No | P | 26.5 x 2.5 | 66.25 |
| 115 | 1 | 55.5 x 2.5 | 138.75 | 24 | Split, Bark pocket and Unsound knot | No | P | 20.5x1.75 | 35.875 |
| 115 | 2 | 50 x 1.75 | 87.5 | 12 | Unsound knot | No | P | 32.5x1.75 | 56.875 |
| | | | | | | | | 16 x 1.75 | 28 |

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| 115 | 3 | 32.5 x 1.75 | 56.875 | 12 | Unsound knot and Hole | No | P | 20.5x1.75 | 35.875 |
| 115 | 6 | 34.5 x 2.5 | 86.25 | 12 | Unsound knot | No | P | 26.5 x 2.5 | 66.25 |
| 115 | 10 | 58.5 x 2.5 | 146.25 | 24 | Split | No | P | 58.5x1.75 | 102.375 |
| 115 | 11 | 10 x 2.5 | 25 | 12 | Unsound knot | No | P | | 0 |
| 115 | 12 | 20.5 x 1.75 | 35.875 | 11 | Hole | No | P | 16 x 1.75 | 28 |
| 115 | 13 | 20.5 x 1.75 | 35.875 | 11 | Hole | No | S | 16 x 1.75 | 28 |
| 115 | 14 | 10 x 1.75 | 17.5 | 24 | Split and Unsound Knot | No | P | | 0 |
| 14 | 1 | 10 x 3 | 30 | 8 | Wane and void | No | P | | 0 |
| 14 | 2 | 16 x 3 | 48 | 8 | Wane and unsound knot | No | P | 16 x 1.75 | 28 |
| 14 | 3 | 16 x 3 | 48 | 12 | Unsound knot | No | P | 16 x 1.75 | 28 |
| 46 | 1 | 44.5 x 3 | 133.5 | 16 | Machining defect | No | P | 34.5 x 2.5 | 86.25 |
| 46 | 7 | 58.5 x 2.5 | 146.25 | 12 | Unsound knot | No | P | 16 x 2.5 | 40 |
| | | | | | | | | 26.5 x 2.5 | 66.25 |
| 46 | 8 | 30 x 2.5 | 75 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| 96 | 2 | 58.5 x 2.5 | 146.25 | 12 | Unsound knot | No | P | 58.5 x 2.5 | 146.25 |
| 96 | 4 | 10 x 2.5 | 25 | 12 | Unsound knot | No | P | 10 x 1.75 | 17.5 |
| 96 | 5 | 58.5 x 2.5 | 146.25 | 24 | Split | No | P | 55.5 x 2.5 | 138.75 |
| 96 | 7 | 26.5 x 2.5 | 66.25 | 12 | Unsound knot | No | P | 26.5 x 2.5 | 66.25 |
| 96 | 8 | 26.5 x 2.5 | 66.25 | 12 | Unsound knot | No | P | 16 x 2.5 | 40 |
| | | | | | | | | 10 x 2.5 | 25 |

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| 96 | 11 | 20.5 x 1.75 | 35.875 | 12 | Unsound knot | No | P | 16 x 1.75 | 28 |
| 96 | 12 | 32.5 x 1.75 | 56.875 | 8 | Wane | No | P | 16 x 1.75 | 28 |
| 120 | 3 | 58.5 x 2.5 | 146.25 | 10 | Bark pockert | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 10 x 2.5 | 25 |
| 9 | 13 | 16 x 2.5 | 40 | 15 | Sound knot | Yes | P | 16 x 2.5 | 40 |
| 3 | 4 | 58.5 x 2.5 | 146.25 | 24 | Split | No | P | 55.5 x 2.5 | 138.75 |
| 3 | 10 | 58.5 x 2.5 | 146.25 | 24 | Split | No | P | 55.5 x 2.5 | 138.75 |
| 10 | 5 | 32.5 x 1.75 | 56.875 | 24 | Split | No | P | 20.5x1.75 | 35.875 |
| 10 | 8 | 34.5 x 2.5 | 86.25 | 12 | Unsound knot | No | P | 26.5 x 2.5 | 66.25 |
| 10 | 9 | 16 x 2.5 | 40 | 10 | Bark pockert and Split | No | P | | 0 |
| 10 | 16 | 10 x 1.75 | 17.5 | 10 | Bark pockert | No | P | | 0 |
| 10 | 18 | 10 x 1.75 | 17.5 | 10 | Bark pockert | No | P | | 0 |
| 10 | 19 | 10 x 2.5 | 25 | 12 | Unsound knot and Hole | No | P | | 0 |
| 82 | 1 | 44.5 x 3 | 133.5 | 24 | Split | No | P | 30 x 3 | 90 |
| | | | | | | | | 10 x 3 | 30 |
| 12 | 1 | 44.5 x 3 | 133.5 | 24 | Split and Hole | No | P | 26.5 x 3 | 79.5 |
| | | | | | | | | 10 x 3 | 30 |
| 12 | 3 | 16 x 3 | 48 | 12 | Unsound knot | No | P | 16 x 1.75 | 28 |
| 12 | 8 | 10 x 1.75 | 17.5 | 11 | Hole | No | S | | 0 |
| 12 | 9 | 16 x 1.75 | 28 | 10 | Bark pockert | No | S | 10 x 1.75 | 17.5 |
| 113 | 1 | 16 x 2.5 | 40 | 24 | Split | No | P | 10 x 2.5 | 25 |
| 113 | 2 | 58.5 x 2.5 | 146.25 | 10 | Bark pockert | No | P | 58.5 x 2.5 | 146.25 |
| 113 | 4 | 32.5 x 1.75 | 56.875 | 10 | Bark pockert | No | P | 10 x 1.75 | 17.5 |
| | | | | | | | | 16 x 1.75 | 28 |

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| 113 | 5 | 58.5 x 1.75 | 102.375 | 12 | Unsound knot | No | P | 50 x 1.75 | 87.5 |
| 90 | 10 | 16 x 1.75 | 28 | 24 | Split | No | S | 10 x 1.75 | 17.5 |
| 93 | 1 | 16 x 2.5 | 40 | 12 | Unsound knot | No | P | 10 x 2.5 | 25 |
| 93 | 4 | 20.5 x 1.75 | 35.875 | 24 | Split | No | P | 16 x 1.75 | 28 |
| 81 | 1 | 26.5 x 2.5 | 66.25 | 14 | Surface check | No | P | 16 x 2.5 | 40 |
| 81 | 5 | 58.5 x 1.75 | 102.375 | 4 | Decay and Unsound Knot | No | P | 32.5x1.75 | 56.875 |
| | | | | | | | | 10 x 1.75 | 17.5 |
| 81 | 6 | 30 x 1.75 | 52.5 | 10 | Bark pockert | No | P | 16 x 1.75 | 28 |
| 81 | 7 | 10 x 2 | 20 | 12 | Unsound knot and Bark pocket | No | S | | 0 |
| 33 | 3 | 10 x 3 | 30 | 24 | Split | No | P | 10 x 1.75 | 17.5 |
| 33 | 8 | 10 x 2 | 20 | 24 | Split | No | S | | 0 |
| 6 | 2 | 44.5 x 3 | 133.5 | 10 | Bark pockert | No | P | 44.5 x 3 | 133.5 |
| 109 | 1 | 44.5 x 3 | 133.5 | 24 | Split | No | P | 26.5 x 3 | 79.5 |
| | | | | | | | | 16 x 3 | 48 |
| 85 | 5 | 10 x 1.75 | 17.5 | 24 | Split | No | S | | 0 |
| | | | | | | | | | |
| | | | | | | | | | |
| 91 | 7 | 58.5 x 2.5 | 146.25 | 16 | Machining defect | No | P | 34.5 x 2.5 | 86.25 |
| | | | | | | | | 16 x 2.5 | 40 |
| 91 | 9 | 58.5 x 1.75 | 102.375 | 12 | Unsound knot | No | P | 50 x 1.75 | 87.5 |
| 91 | 13 | 26.5 x 2.5 | 66.25 | 12 | Unsound knot | No | P | 2.5 x 26.5 | 66.25 |
| 91 | 17 | 10 x 2.25 | 22.5 | 12 | Unsound knot | No | S | | 0 |
| 94 | 2 | 16 x 3 | 48 | 10 | Bark pockert | No | P | 10 x 3 | 30 |
| 94 | 7 | 10 x 1.75 | 17.5 | 9 | | No | S | 10 x 1.75 | 17.5 |

| Board | Part | Dimension (in. x in.) | Area (sq. in.) | Defect Type | Defect description | Allo-wed | Pri-mary | Salvage (in. x in.) | Area (sq.in) |
|---|---|---|---|---|---|---|---|---|---|
| 60 | 3 | 58.5 x 2.5 | 146.25 | 12 | Unsound knot | No | P | 55.5 x 2.5 | 138.75 |
| 70 | 3 | 44.5 x 3 | 133.5 | 10 | Bark pockert | No | P | 44.5 x 3 | 133.5 |
| 70 | 6 | 16 x 2.5 | 40 | 10 | Bark pockert | No | P | 10 x 2.5 | 25 |
| 110 | 1 | 26.5 x 2.5 | 66.25 | 24 | Split | No | P | 16 x 2.5 | 40 |
| | | | | | | | | 10 x 2.5 | 25 |
| 104 | 2 | 16 x 3 | 48 | 12 | Unsound knot | No | P | 16 x 3 | 48 |
| 5 | 4 | 10 x 1.75 | 17.5 | 24 | Split | No | S | | 0 |
| 97 | 6 | 26.5 x 2.5 | 66.25 | 10 | Bark pockert | No | P | 16 x 2.5 | 40 |
| | | | | | | | | 10 x 2.5 | 25 |
| 97 | 7 | 10 x 2.75 | 27.5 | 24 | Split | No | S | | 0 |
| 97 | 8 | 20.5 x 1.75 | 35.875 | 10 | Bark pockert | No | S | 16 x 1.75 | 28 |
| 97 | 9 | 32.5 x 1.75 | 56.875 | 24 | Split | No | S | 30 x 1.75 | 52.5 |
| | | Total volume (BF): 72.4 | Total area (sq.in.): 10423.5 | | | | | Total volume (BF): 57.0 | Total area (sq.in.): 8210.5 |

# VITA

**Name**: Agus Widoyoko Agus Widoyoko

**Place and Date of Birth**: Trenggalek, East Java, Indonesia; August 17, 1962

**Education**
- Completed Master of Science in Wood Science and Forest Products, Virginia Polytechnic Institute and State University, March 1996. Thesis: Optimum Lumber Processing in Furniture Rough Mill.
- Attended Diploma Course on Wood Processing Technology in Finland, 1991.
- Attended Diploma Course on Follow-up Teacher Training on Sawmilling in Tanzania, 1990.
- Attended Diploma Course on Teacher Training on Sawmilling in Finland, 1987.
- Attended Diploma Course on Sawdoctoring in Samarinda, Indonesia, 1986.
- Completed Bachelor of Science in Forest Product Technology, Bogor Agriculture University, March 1985.

**Scholarship received**: OTO-BAPPENAS, the Indonesian Government Scholar, 1993-1995.

**Work Experience**:

- Teacher and instructor in Samarinda Forestry Senior High School and Samarinda Forestry Training Center, 1986-1993.
- Counterpart of FINNIDA's consultant, Samarinda Forestry Training Center, 1987-1991.