# A Machine Vision System for Automatically Grading Hardwood Lumber

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## Abstract

Any automatic system for grading hardwood lumber can conceptually be divided into two components. One of these is a machine vision system for locating and identifying grading defects. The other is an automatic grading program that accepts as input the output of the machine vison system and based on these data, determines the grade of a board. The progress that has been made on developing the first component the machine vision component will be reported in this paper. The machine vision system being developed is made up of an imaging subsystem for imaging rough lumber surfaces, a computer vision subsystem for analyzing the image data and identifying grading defects, a materials handling subsystem for moving boards through the imaging devices, and, finally, a computer for executing the algorithms comprising the computer vision subsystem and for controlling the other subsystems. This paper will describe the progress that has been made on developing all of these components. It will also indicate the directions for future research. A major god of this research activity is to create a vision technology that will be applicable to not only the grading of hardwood lumber but a number of other forest products related applications as well.

## Introduction

Any automatic system for grading hardwood lumber is composed of two components. One of these is a machine vision system that can locate and identify grading defects. The other component is an automatic grading program that accepts as input the output of the machine vision system and, based on these data, determines the grade of a board. This program is a computer algorithm form of the National Hardwood Lumber Association (NLHA) hardwood grading rules. Its development has entailed translating the English statements appearing in the NLHA grading rules into precise mathematical statements that can be understood by a computer. A good deal of progress has been made on developing this program [1-3].

This paper reports the progress that has been made on developing the other component of an automatic grading system, the machine vision component. The machine vision system being developed is composed of an imaging subsystem for imaging board surfaces, a materials handling subsystem for moving boards through the imaging subsystem, a computer vision subsystem that analyzes board image data to locate and identify grading defects, and a computer for executing the algorithms that comprise the computer vision subsystem and for controlling the other subsystems of the machine vision system.

Of all the components that comprise the machine vision system, the one that is the most difficult to design is the computer vision subsystem. There are a number of reasons for this. First, for a grading system to be truly robust, it must be able to handle a variety of different hardwood species. But hardwood species vary significantly in their appearance. Grading defects in hardwood lumber manifest themselves in many different ways. For an automatic system to be industrially useful requires that it be able to process lumber at least as fast as a skilled human grader. This means that the vision system must be able to analyze image data at a rate of at least two linear feet per second, i.e., so it can grade a 16 foot board in 8 seconds. Lastly, since grading depends on detecting small grading defects, the vision system must be able to process high spatial resolution image data. The need for high spatial resolution data together with the rather high flow rates mean that the algorithms comprising the computer vision subsystem must analyze lots of data fairly quickly. To minimize total system costs the computer vision algorithms must be structured so that they minimize the computational complexity of the analysis task. Only in this way can a reasonably “inexpensive” computer be used to perform the processing.

All these requirements taken together pose a challenge to the developer, especially considering the state-of-the-art of computer vision. Developing computer vision algorithms is an art and not a science. At the beginning of any computer vision related research activity there is no assurance that a complete computer vision system for solving an applications problem can be created. Given this fact, prudence demands that one proceed cautiously. This implies that one must first establish the feasibility of creating the required computer vision methodologies. Also, the initial research should employ standard off-the-shelf imaging hardware and computing system so as to minimize initial hardware costs.

This paper will report the results of the initial investigations that have gone into developing the computer vision subsystem. It will show some of the processing results that have been obtained. It will be argued that these results do indicate the feasibility of creating a computer vision system that can locate and identify grading defects on rough hardwood lumber.

The initial research has employed standard off-the-shelf hardware. The 512x480 standard RS-170 solid state camera used in the initial investigations restricts the research by allowing only images of 8 inch by 8 inch square areas of board surfaces to be considered. The use of this hardware is the limiting factor in proceeding further. To proceed further requires access to images of full sized material, i.e., boards up to 16 feet long, up to 13 inches wide, and up to 2 1/4 inches thick.

Currently, a full scale prototype machine vision system is being developed. This system will combine all the components of a machine vision system so that a variety of experiments can be performed. AS was stated above, developing computer vision algorithms is an art and not a science. A good deal of experimentation is required to develop robust methods. The experimentation performed must reflect the type of material the algorithms will have to analyze in the industrial setting. Practically speaking, the feasibility of the complete machine vision system cannot be established until issues of maintainability and reliability are addressed. Also, in any automated system, hardware and software must interact. Compromises must be made between what can be accomplished with hardware and what can be accomplished with software. A complete systems approach is required in the development process. This full scale prototype will allow all these issues to be addressed.

The major thrust of the current research activities is developing this full scale prototype. The development of this prototype is very important. It provides a vehicle for performing research on a number of forest products related problems and not just the development of an automatic grading system. Currently, two problem domains are being considered. One is developing a machine vision system that can be used to automatically grade lumber. This will be referred to as the rough lumber problem, since any grading system must be able to handle rough lumber. A second problem is developing a system that can be used to automate the rough mills of hardwood furniture and fixture plants. This will be called the surfaced lumber problem, since most furniture and fixture plants, at least, skip plane material prior to cutup. An important goal of this research activity is to develop methods that have general applicability within the forest products industry. Considering both of these problems simultaneously provides an excellent opportunity to develop general purpose methods. This paper will report the progress that has been made on developing this prototype.

## Computer Vision Subsystem Development

### *The Rough Lumber Grading Problem*

A machine vision system for grading hardwood lumber must be able to handle rough lumber. Developing computer vision methods for locating and identifying grading defects on rough lumber is a difficult problem. This problem is arguably more complex than the computer analysis of images of surfaced lumber since surfacing removes a good many of the discolorations that routinely appear on rough lumber. For example, there is the variability in exposure to ultra-violet radiation. After lumber is sawn it is typically stacked, usually outside, where the stack is exposed to direct sunlight. Boards on the exterior portion of the stack receive signifcant exposure to ultra-violet radiation while boards on the inside of the stack receive very little exposure to ultra-violet light. This difference in exposure can and does cause a marked variation in material appearance depending on a board's location within the stack [4]., Light surfacing removes any such color variations.

Stacks stored outside are exposed to the weather. This weathering can also cause variation in the visual appearance of a board, again depending on its location in the stack. Again, light surfacing removes the discolorations caused by weathering.

There is also the problem of boards getting dirty during the various materials handling operations that occur prior to grading. Obviously dirt can be mistaken for a grading defect. Most graders carry a knife to ensure that a particular spot on a board is not just dirt that can be scraped off, but a real grading defect. A machine vision system will not have access to a knife. Surfacing just prior to machine vision inspection removes all dirt and prevents the machine vision system from having to recognize dirt.

Even the drying process introduces potential color variations in the material. Sap can come out of lumber and dry on the surface. The stickers used to separate the boards during drying can leave marks on the material, etc. The rough surface itself can cause problems. The lighting needed to create a digital image of the board can cast shadows. These shadows could be misinterpreted by computer vision algorithms as being a defect. It is also known that the extent of surface roughness can affect the color of the material [5]. Surfacing creates a relatively smooth surface, free of sap stains and sticker marks.

As was stated in the introduction, more and more secondary remanufactures are surfacing the material prior to cutup in the rough mill. These manufacturers do it to simplify the cutup operation for the sawyers. Surfacing makes defects, especially small defects, easier to see. The fact that surfacing is used in the rough mill is another indication of the relative difficulty of the two analysis problems.

Finally, the computer analysis of rough lumber for the purpose of grading must cope with the problem of surface moisture. Lumber can be graded right after it is first sawn to sometime after it is kiln dried. The variation in surface moisture content during this period of time is substantial and is known to cause a significant variation in the visual appearance of the material [6]. This is another problem that need not be considered in rough mill automation since boards cutup in rough mills have all been dried.

***Initial Problem Statement***

Because of the complexity of the rough lumber inspection problem, it was decided to reduce the complexity somewhat in the initial investigations by considering a less general problem. A decision was made to concentrate on just three species: red oak, cherry, and yellow poplar. Only fairly clean boards were selected for the study. Boards with mud spots on them were not included in the data base. Boards with sticker marks were allowed. Badly weathered boards were not. Boards containing areas discolored by ultra-violet light were also not considered.

The boards selected were digitized using a standard black and white RS-170 solid state camera having a resolution of 512x480. Full color images were obtained by using red, green, and blue color falters. The resulting full color images had a spatial resolution of approximately 64 points per inch so that each image represents approximately an eight inch by eight inch area.

The process of digitizing an image is referred to as “scanning.” To scan an image one must select a number of scanning parameters. These parameters correspond to setting the f-stop and exposure time on a 35 millimeter camera. For a vision system to be species independent the same scanning parameters have to be used to image all the material examined. Hence one set of scanning parameters must be used to image all the various hardwood species. Using one set of paramaters means that each species will not be “optimally” imaged just as one setting for the f-stop and exposure time will not optimally image all pictures one might want to take. The concern in using just one scanner setting is that the images created could be so poor as to make the analysis of these images computationally complex for the computer.

To determine the effects of scanning parameter settings, a number of boards from each species were scanned twice. The first image of each board was created using scanning parameters “optimized” for that board’s species. The second image of each board was created using scanner settings that allow all hardwood species to be imaged. This last set of scanner settings has been used to scan surfaced boards of red oak, white oak, hickory, poplar, maple, walnut, cherry, mahogany, and white pine.

Finally, another small number of rough samples of red oak were scanned when their surfaces had varying degrees of surface moisture content. The procedure followed was to wet the surface of each sample by letting the sample soak in water for some time. The samples were then removed from the water and scanned at regular time intervals. The purpose of this set of data was to determine the effects of surface moisture on the computer analysis of the images.

The goal of these studies was to draw from the experience that has been gained from the study of surfaced lumber [7-12] and to see if the same basic technology could be used on both problems. In those areas where difficulties occurred, the objective was to create algorithms that will work on both rough and surfaced lumber.

The image data used in the initial studies was color image data. Color characteristics of board features play an important role in the cutup operation performed in the rough mill. Because of this, a good deal of research had gone into the use of color data prior to considering the rough lumber grading problem. Another reason for selecting color imagery is that humans can perform both grading and saw up based solely on input of color information from the eye. Therefore the initial concentration on color imagery seems well founded.

***The Segmentation System for Color Imagery***

To achieve an inexpensive real-time implementation of the computer vision subsystem means that efforts must be made to reduce the computational complexity of these algorithms, to make them as computationally simple as possible. One method for reducing computational complexity comes from the studies that have been conducted on surfaced lumber [7-12]. The idea is a simple one and comes from a cursory analysis of the problem. The imaging subsystem of the machine vision system must have a field of view as wide as the widest board that should be processed. Studies show that over 99 percent of most hardwood lumber is less than 13 inches wide. So this would seem a reasonable field of view. Yet the average hardwood board has a width of between 6 and 7 inches. If one can easily separate pixels of background from those of board, a substantial reduction in the amount of data that needs to be processed by the recognition algorithms can be achieved. Next, if one looks at a typical board the vast majority of the board surface is clear wood, free of all defects. If one can create computationally simple methods for separating areas of clear wood from areas that might potentially contain a defect, another substantial reduction would occur in the volume of data that has to be processed by the recognition algorithms. This savings becomes particularly important if one considers that recognition algorithms are always the most computationally complex of any the algorithms appearing in a computer vision system. By limiting the volume of data that has to be processed by the recognition algorithms the computational complexity of the whole analysis problem can be markedly reduced.

If this simplification method is employed, then the resulting vision system software can best be conceptually divided into two parts, a Segmentation System and a Recognition System. The purpose of the Segmentation System is to separate picture elements, “pixels,” of background from pixels of board, and pixels of clear wood from pixels of potential grading defects. The objective is to use very simple algorithms for performing each of these tasks. The purpose of the Recognition System is to identify the type of defect present at the locations marked by the Segmentation System. The goal of the Segmentation System is to reduce the volume of data that must be processed by the Recognition System.

Approximately two years of effort have gone into developing robust methods for performing the segmentation operation, though admittedly, the thrust of these efforts has gone into the segmentation of surfaced lumber. The general methods used are described in References 7 - 12. However, the methods reported in these references had trouble separating decay and blue stain from areas of clear wood. Since the publication of these articles a new method has been devised [13,15]. It has yielded significantly improved results and has been used, without alteration, to segment images of surfaced red oak, white oak, hickory, poplar, maple, walnut, cherry, and white pine.

A goal of this study was to determine whether this new segmentation method would also work on rough lumber. Obviously, there is a strong theoretical motivation for wanting similar methods to be used on both problems. The overall objective is to create a vision technology that is applicable to a variety of forest products applications.

***The Recognition System for Color Imagery***

The purpose of the Recognition System is to identify the type of defect present at a particular location, a location provided to the Recognition System by the Segmentation System. In computer vision terminology the Recognition System performs the “scene analysis” operation, i.e., given a particular image region the purpose of the Recognition System is to assign a label that identifies what is present in that region.

Conceptually, there are three basic approaches to scene analysis [16]. The first of these is the bottom-up type of approach. Using a version of this type of approach image data is processed by a number of different operations, each operation producing a new data structure that makes some new facet of the image explicit to the computer. The last of the operations performed are those that actually label the regions of the image.

Bottom-up approaches have their origin in very early computer vision research [17-19]. Bottom-up approaches are known to be very sensitive to noise. Any mistake made by an early processing operation propagates up through the rest of the processing operations. As such this type of approach has proven ineffective on real world images [16], e.g., images of rough lumber.

A second class of scene analysis strategies are the top-down methods. The basic idea behind a top-down method is the formulation of a hypothesis of what is in the image. Once the hypothesis has been made operators are applied to the image to verify whether the formulated hypothesis is correct. Note that the initial hypothesis is generated without using any information collected from the scene. Further if the results of an operation disprove the current working conjecture of the scene analysis system then another working conjecture or hypothesis is generated. The generation of this new hypothesis is also independent of any information obtained from the scene during earlier processing.

Because no image derived information is used in formulating working hypotheses, top-down methods are very limited in their generality [ 16]. However, these approaches have been successfully used on very complicated albeit highly structured real world scenes, e.g., the analysis of chest radiographs [20].

The third class of scene analysis strategies is the combination or heterarchical strategies. Such strategies use a combination of both bottom-up and top-down methods. It can be argued that human vision uses a combination strategy. The need for some bottom-up processing where image derived information is used to guide the analysis should be intuitively clear. The need for a scene analysis system to make an hypothesis and attempt to verify that hypothesis using special operators is not so intuitively clear. See Reference 16 for an argument indicating the importance of top-down processing in human vision.

The final Recognition System being developed for the rough lumber inspection problem will use a combination strategy. Bottom-up type operations are used initially. The culmination of the bottom-up operations is a labelling of the various regions found in the image. For each region, the bottom-up derived labelling is used as the current working hypothesis for the top-down type of analysis that comes next. Ideally, an examination of the current working hypothesis could be found to be erroneous by the operators applied to test the hypothesis. If this happens additional bottom-up processing would be required to generate a new working hypothesis for the region. This new working hypothesis would then be used in a top-down analysis, etc. Obviously, such a recognition procedure will work in real-time only if a very few iterations are required before a correct label, i.e., defect type, is assigned.

As of this writing the Recognition System is not completely developed. It has only been trained to identify splits/checks, knots, holes, and wane. Also, the system does not contain all the required topdown components. It does contain a significant amount of the required bottom-up processing. The system is rule base, uses neural networks to validate the final working hypothesis about the identity of a defect at a particular location, and uses fuzzy logic to help focus attention of the recognition algorithms.

***Initial Study Results***

The analysis of the moistened red oak samples confirmed the results given in Reference 6. Clearly, surface moisture content can significantly affect wood color. More importantly, it was found that the color difference between clear wood and grading defects changes markedly with surface moisture content. When surface moisture is high there is very little color difference between clear wood and many of the grading defects. As the surface dries this color difference becomes much more pronounced. Hence whether man or machine is doing the grading, the grading can be accomplished more easily and with greater accuracy if board surfaces are allowed to dry [13-15]

It was this result that motivated the consideration of kiln dried lumber in this study. Such samples have low surface moisture content and are dimensionally stable. Dimensional stability of the samples was an important consideration in selecting kiln dried lumber. Dimensional stability of the samples simplifies efforts to verify the accuracy of an automatic analysis.

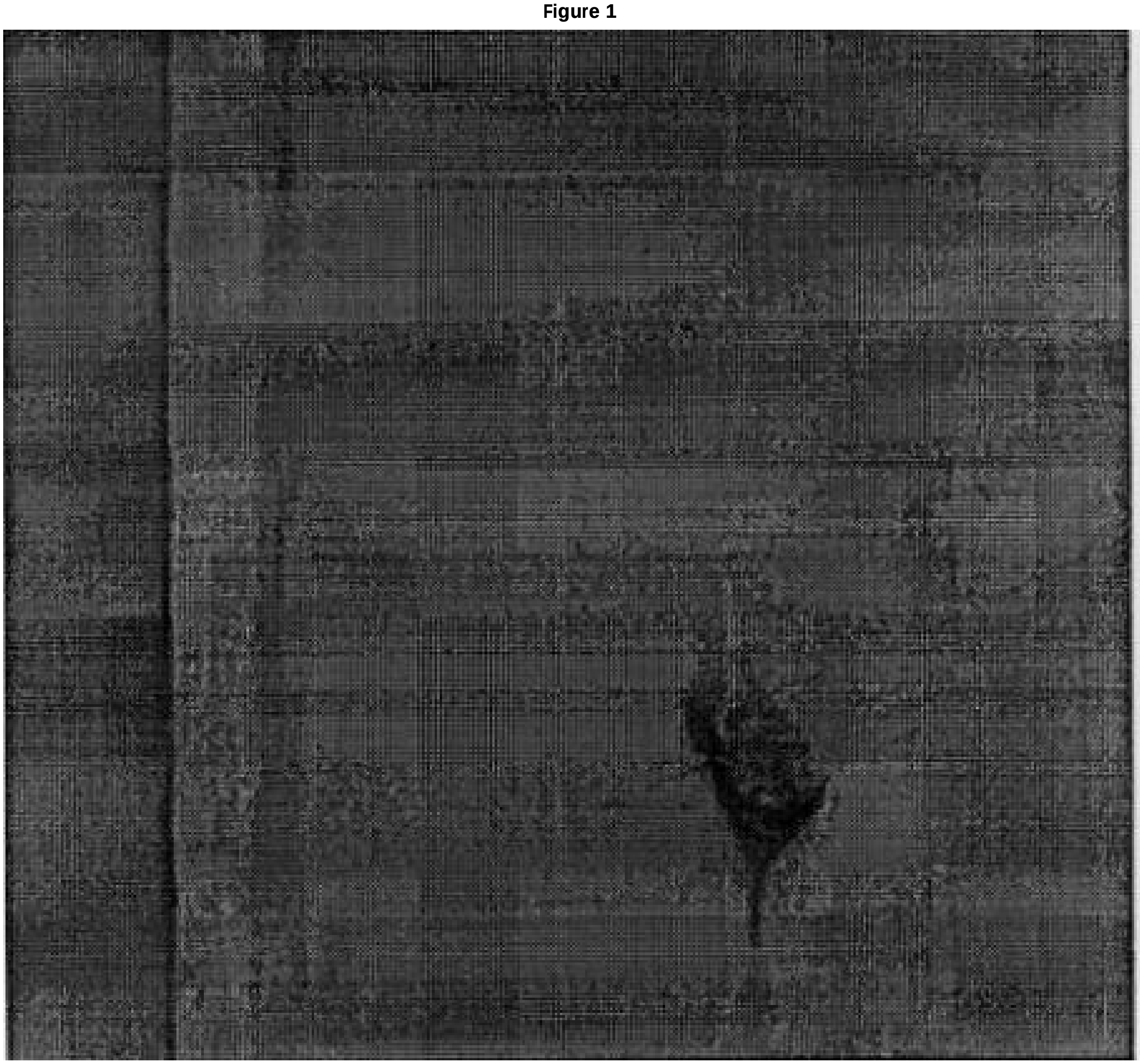
The application of the previously developed segmentation methods to the rough lumber samples showed that these techniques work almost as well on rough lumber as on surfaced lumber. There is some slight degradation in quality caused by the shadows cast by the rough surface of the material [13-15].

The results obtained from the segmentation methods did not depend on the scanning parameters used. Hence, this study, just like the study involving surfaced samples of red oak, white oak, cherry, maple, walnut, poplar, hickory, and white pine, indicates that a single scanner setting for all hardwood species can be used. This is a very important result with regard to the possibility of achieving species independent processing [13-15].

Next, the segmentation methods work equally well across the spectrum of hardwood species that have been tested to date. Both this study and the one done on surfaced lumber samples show the robustness of these methods and their ability to be applied to any species and obtain good results. Again this is a very important result with regard to creating species independent processing methods [13-15].

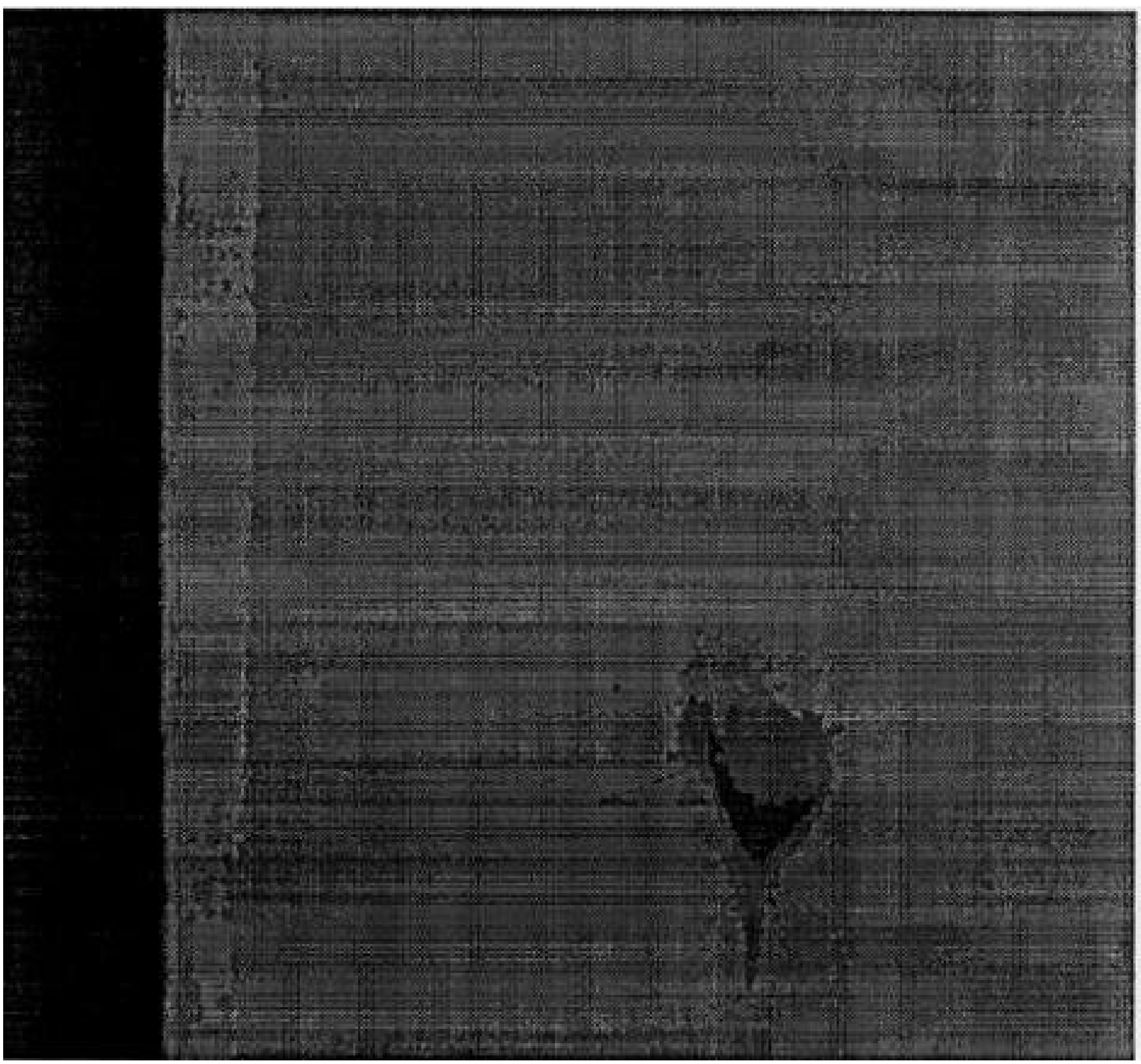
The most important results to be presented are those obtained by applying the partially developed Recognition System to rough lumber data. Consider the board image shown in Figure 1. This is a black and white version of the color image used in the actual processing. This image is of a rough

Figure 1



poplar sample. Figure 2 shows the results obtained from the initial segmentation operation performed by the Segmentation System. At this point in the processing, the computer knows on a pixel-by-pixel basis to which of 6 possible classes each pixel in the image belongs. Both the number of classes as well as the rules for assigning a class to each pixel are determined automatically by the segmentation methods in the Segmentation System. The black area represents the “background class.” This assignment is easy because one can control the color of the background and hence easily train the computer to recognize this color. The other 5 classes represent areas of different but approximately uniform color. Note that the Segmentation System is able to detect the color difference between heartwood and sapwood. Also, note that it has detected three different classes that together comprise the knot on the board.

**Figure 2**



As of this point the system believes that the class shown in medium gray, i.e., the heartwood, is the clear wood area. It believes that this class is the clear wood class because there are always more pixels of this clear wood than any other class. This follows from the fact that the largest portion of any board is clear wood area whether this clear wood be heartwood or sapwood.

Note that the purpose of the Segmentation System is to detect areas that might contain a defect. It does not have to find the exact boundary of a defect, only an approximate one. Nor does it have to be completely noise free. If it makes errors these errors will be compensated for later in the processing.

Further bottom-up processing is performed by the Segmentation System to determine the number and location of the connected regions appearing in the segmented image. The boundaries of the various connected regions found are shown in Figure 3. Note that prior to this processing the computer only knew on a pixel-by-pixel basis to which class each pixel belonged. It also knows which class seemingly corresponded to clear wood. The result of this new processing is to make explicit to the computer the number and location of connected regions.

An examination of Figure 3 shows that the initial segmentation did produce some erroneous results. Most of the "noise" in the segmented image is confined to very small connected regions. Hence the next operation performed by the Segmentation System is to merge these small regions

Figure 3

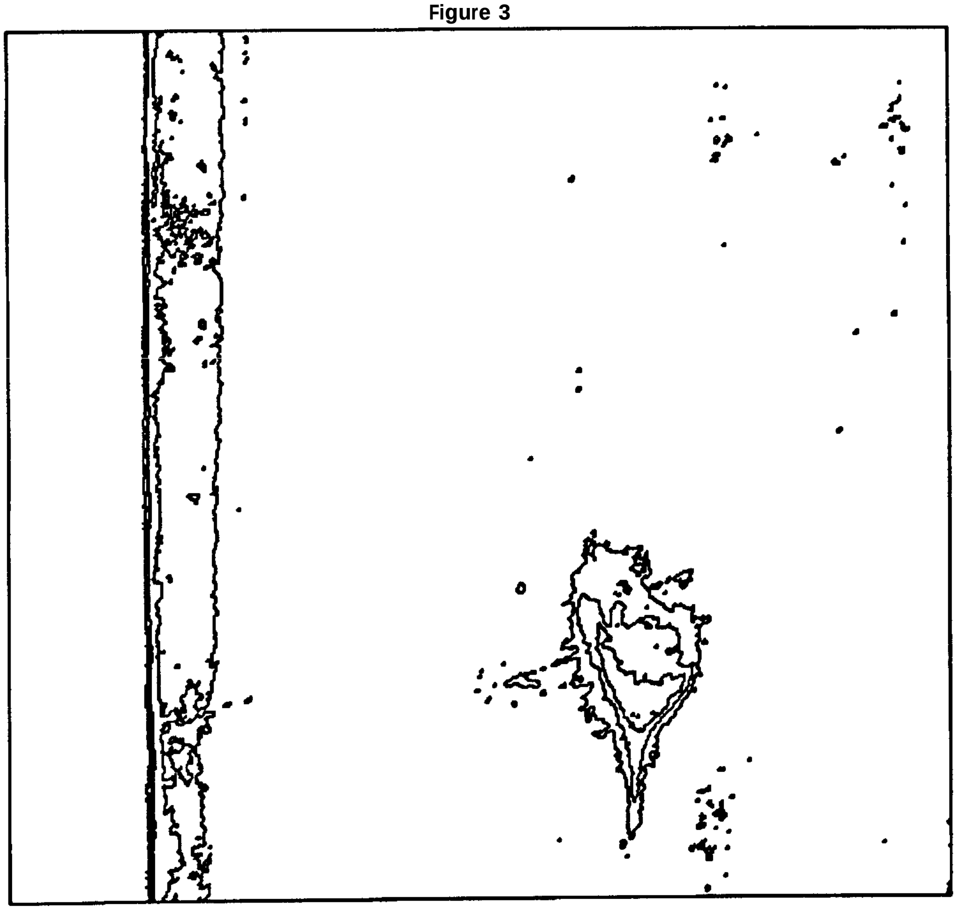
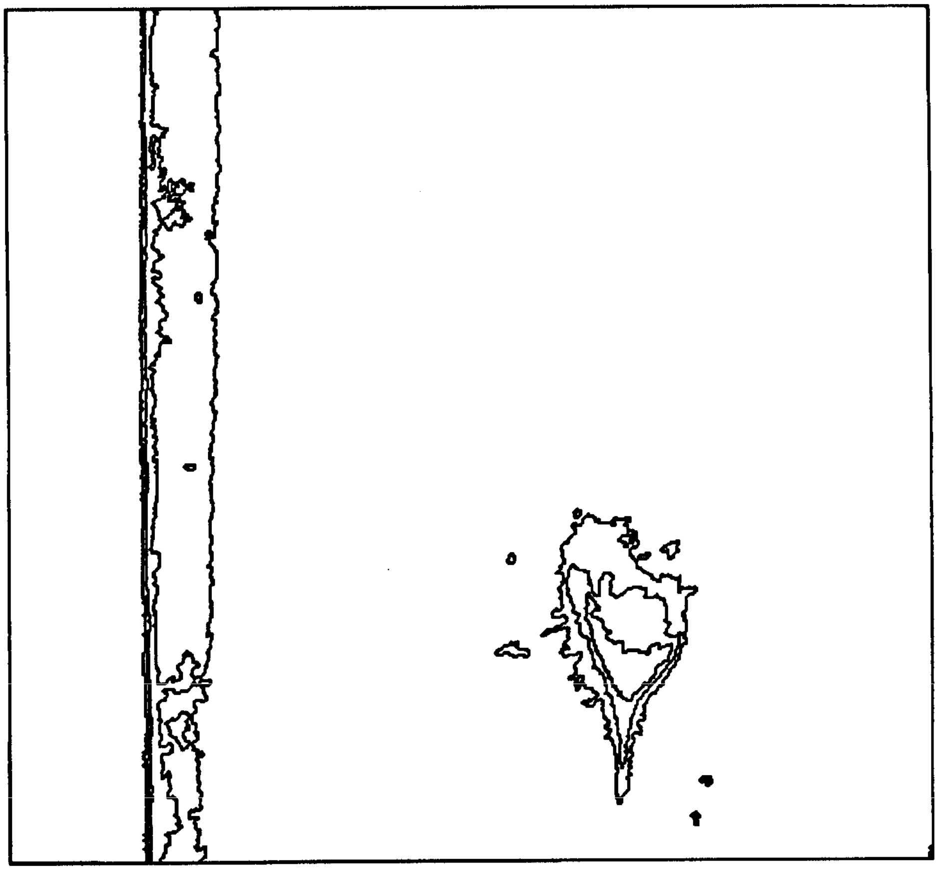


Figure 4



with larger ones. Two tests are employed to do this merging. After all the merging that can be done is completed, each of the resulting connected regions has a list of properties computed from it and these properties are put in the region's attribute table.

The first processing step of the Recognition System is again a bottom-up one. Each region in Figure 4 is first given a label based on the properties in the attribute list. Adjacent regions having the same label are merged together to form the concept of DEFECT_OBJECT. An attribute table of the merged regions is computed and associated with the DEFECT_OBJECT. The initial labeling of the DEFECT_OBJECTs is then verified based on updated attributes together with additional properties computed from the DEFECT_OBJECT using neural networks.

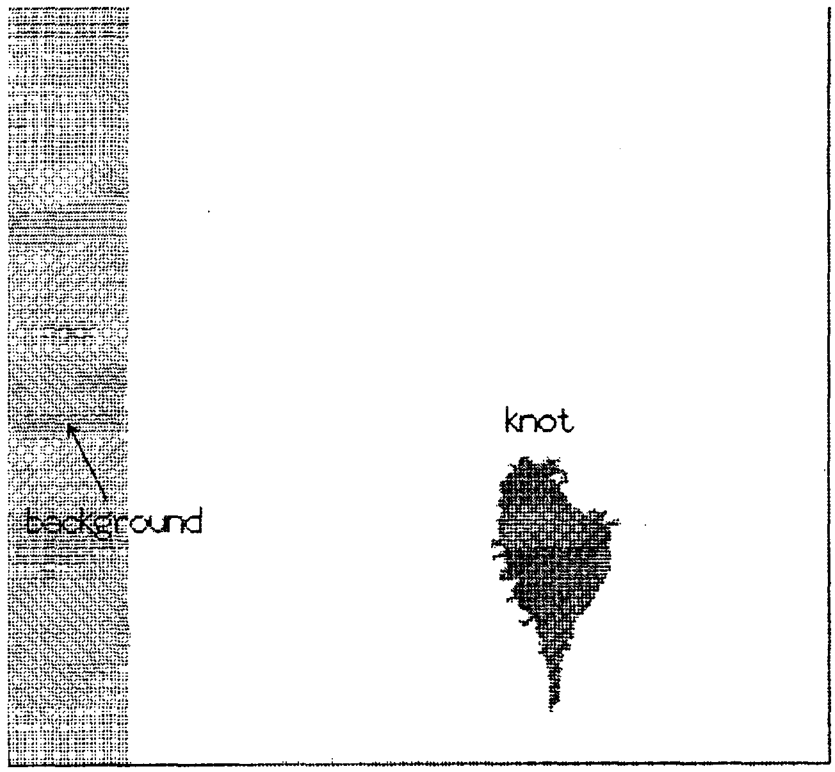
The process of creating DEFECT_OBJECTs is done by independently operating defect recognition modules. Each of these modules is an "expert" in identifying one particular type of defect.

The resulting labelling can still have errors. To remove such errors a top-down type processing is used. For a particular DEFECT_OBJECT this processing uses, as its working hypothesis, the label that was assigned to the DEFECT_OBJECT during the bottom-up processing.

The results obtained after applying the existing top-down type processing are shown in Figure 5. Note that the light gray area shown in the Figure 5 is the region of the image that the Recognition System believes to be background. The labelling of the background region was actually performed by the Segmentation System. The white area of the figure is the region that the Recognition System believes is clear wood, i.e., either heartwood or sapwood. The darker gray area in the figure is the region that the Recognition System believes is knot.

Approximately two years of effort have gone into creating the current recognition system. Much has been learned. Much remains to be done. For more information on this recognition system see References 21-23.

Figure 5




***Problems***

The primary focus of the research in hardwood defect detection has been in handling surfaced lumber for the purpose of automating rough mill cutup. The thrust of this work was on being able to locate a number of defects including badly discolored wood. Defect removal in the rough mill is largely based on removing aesthetically displeasing areas so that such areas will not appear in rough parts. This motivation led to considering color cameras as the transducer to use to image rough boards for purposes of grading lumber.

All the experiments performed to date do indicate that color imagery is useful in defect detection. The computer vision methods described in the last section progressed surprisingly fast given the *a priori* perception of problem difficulty. It has worked remarkably well on the simplified problem to which it was applied. Unfortunately, the rough lumber problem in its full generality is a very difficult problem. Dirty material can and does confuse the segmentation method that has been created. Experiments with other segmentation methods have yielded no better results. The shadows cast by the rough surface can and do reduce the sensitivity of this and other segmentation methods. Even in surfaced lumber there are knots that have the same color as clear wood. This situation is further exacerbated in rough lumber. Wane detection is no problem as long as cambium is intact. But if debarkers are used, the cambium frequently comes off with the bark not to mention some sapwood as well. In such cases, wane is difficult both to detect as well as to identify.

It is currently believed that color information alone is not enough. Color imagery requires that defects be detected in an indirect manner. That is, one attempts to infer the presence of a defect and identify it based on non-unique characteristics, e.g., knots are typically reddish brown but a bark pocket can be the same color. And, as was mentioned above, knots can be the same color as clear wood. Hence, it is possible for a defect to evade detection in color imagery and, even if detected, evade being correctly identified.

It all leads the authors to believe that other imaging scanners are needed to augment color cameras. To aid in knot detection an x-ray scanner would seem useful. Experiments performed at Virginia Tech indicate that x-rays provide an effective way to detect the presence and extent of knots. X-ray scanners are currently being used by some softwood companies to aid in the automatic grading of 2x4 lumber. X-ray scanners seemingly provide a direct method for locating and identifying knots. For boards of uniform thickness X-ray scanners can directly measure the density differences that exist between knots and clear wood. But even the addition of an x-ray device might not be enough.

Variations in x-ray attenuation can come from a variety of sources, most particularly board thickness. A welcome addition to the color camera systems and x-ray scanner would be a system for gauging board thickness. A new scanning system is being designed at Virginia Tech to do just that. This new scanner can detect any defect that affects measurement of board thickness, e.g., holes, wane, and splits/checks, etc. Experiments with a simplified version of this scanning system have shown it to be effective in locating and identifying all these defects. Again, this scanning system is able to detect these defects in a non-invasive manner based on differences in measured thickness of a board.

Obviously, each new scanner added to a machine vision system increases the cost of the system by the amount that the scanner costs. An objective in adding new scanners is to improve overall system performance so that the additional price is offset. Another objective is to add scanner systems that will make the analysis problem less computationally complex. Reducing the computational complexity can markedly reduce the cost of the computing hardware needed to analyze the image data in real-time. A final objective for adding a scanning system is to make the analysis problem solvable.

Based on the results that have been obtained to date, it seems impossible to accurately locate and identify grading defects of typical rough lumber coming out of a sawmill using only color image data regardless of the computational complexity of the algorithms employed. To solve this problem is going to require additional scanners. These scanners must improve the results obtainable when only color data is used. These improved results should help offset their costs. They should also reduce the complexity of the computer vision analysis tasks, thereby reducing the cost of the computer needed to process image data in real-time.

Integrating information from color cameras, an x-ray scanner, and the new “range” scanning system should markedly improve the quality of the results obtainable from automatic analysis. Interestingly, these new scanners also provide an effective tool in the analysis of surfaced lumber for rough mill automation. It is also known that they will prove useful on a variety of other forest products related applications as well. However, the question remains, will they be enough? Currently, it is believed that they will, but further study is needed to ensure that this is the case.

Lastly, it must be pointed out that for each new scanner added, the computer vision subsystem will have to be adapted to handle data from this new imaging device. Obviously, this adaption will require some time. However, the objective in adding each new scanning system is to reduce the complexity of both the software and the software development effort.

## Hardware Development

Excluding the computer vision subsystem, the rest of the prototype machine vision system is all hardware. This hardware includes the imaging subsystem, the materials handling subsystem, and the computer system that will process the computer vision algorithms and control all the other hardware subsystems. As was stated in the introduction, there area number of reasons for wanting to create a full scale prototype. One reason is to examine the hardware/software trade-offs in designing a commercially viable machine vision system. As was indicated in the last section, one hardware/software trade-off concerns the number and types of imaging systems that must be used. Currently, it appears that using just color data makes it very difficult if not impossible to create a computer vision software system that can accurately locate and identify grading defects on rough lumber or that can detect removable defects on surfaced lumber for rough mill automation. Therefore, to solve these problems additional hardware is needed, i.e., additional imaging systems, so that the software design problem can be simplified and solved. Actually, there are a number of uncertainties involved in both the hardware and software components of this machine vision system. Currently, data is insufficient to allow one to determine exactly what spatial resolutions should be used with each of the scanning devices to be employed in this machine vision system. This is a critical point since the lower the spatial resolution the less computationally complex the analysis problem. There is also an uncertainty as to how accurate the machine vision system must be. Clearly, it should be as accurate as a human grader, but how accurate is the human grader? These same basic questions remain unanswered in the rough mill automation problem as well.

The purpose of the prototype system is to resolve these uncertainties for both problems. Within the context of the aircraft industry this prototype is an experimental plane. Its goal is to probe the frontiers and provide the data upon which commercially viable systems can be created. And just as in the case of the aircraft industry, experimental planes inevitably cost more than commercial aircraft whose design was based on the data obtained from the experimental plane. This additional cost factor follows from the fact that there are so many uncertainties. Hence, the experimental prototype must be over designed. The data collected by this system will probably be of a higher spatial resolution than that used in a commercial machine vision system. The number of sensors employed will probably be greater than that used in a commercial system. The computer employed will probably be more expensive than the ones that will be used on commercial systems.

The primary design criteria for creating the prototype are simple. One must allow for almost every eventuality. The subsystems must be flexible enough to provide a mechanism for change. The prototype must provide a vehicle for resolving the many uncertainties associated with designing and building a commercially viable system for automatically grading hardwood lumber or for automating the rough mill of furniture and fixture plants. The authors feel that the design for this prototype accomplishes all these objectives.

In what follows the design and development of each of these hardware subsystems will be described in some detail.

***Imaging Subsystem***

As was mentioned above, the imaging subsystem is going to be comprised of a number of imaging sensors. Of all these imaging sensors, the one farthest along in the development phase is the color imaging subsystem. A color line scan camera has been selected. This Pulnix camera has a resolution of 864 color pixels. At 64 points per inch spatial resolution this camera will allow a 13 1/2 inch field of view, a field of view wide enough to handle the vast majority of hardwood lumber. The camera can run at 2.5 megahertz. At this speed the camera can generate images that have 64 points per inch cross board resolution and 32 points per inch down board resolution. Tests indicate that this is more than enough spatial resolution for most forest products related applications, especially for automatic grading and rough mill automation. Two of these cameras have been purchased, one for scanning each of the two board faces. For more information about the motivation for selecting these cameras see References 23-25.

Light sources for illuminating board surfaces have also been selected. These sources use tungsten-halogen incandescent bulbs that have a color temperature of approximately 3600 Kelvin. The light from a bulb is transferred through a fiber optic cable that is composed of a number of very thin fiber optic light lines. At the far end of this cable the individual fiber optic lines are stacked on top of one another with their ends forming a straight line. These fiber optic lines are all enclosed to keep them permanently in this configuration. These light sources are produced by the Fostec Corporation. There are a number of motivations for using this type of light source [ 12,24, 25], one of which is that they provide a convenient method for changing bulbs that burn out.

The cameras and light sources have all been mounted on an imaging system "prototype." This prototype is a 4x6 feet optical bench in a free standing enclosure. A simple 6 feet long computer controlled linear stage is used to transport boards up to 4 feet long through the color camera systems. Both cameras were initially connected to the PS/2 via a rather low speed parallel interface, an interface similar to the one typically used to connect a printer to a computer. This easy to design interface has allowed experiments to be conducted using these cameras while more complicated interface hardware was being designed, built and tested. For more information about the progress that has been made on developing the color imaging components see References 12,24, and 25.

This more complicated hardware is a high speed interface that allows both color cameras to be connected to a PS/2 Model 80. It provides the mechanism for collecting the color imagery and storing it into computer memory [26]. This interface will allow the collection of color imagery data as fast as it can be generated by the camera systems, i.e., 2.5 megahertz.

his "prototyper" has allowed various imaging geometries to be tried. It has allowed the illumination problems to be solved. Basically, it will allow all the components of the color scanning system to be checked out. Once completely checked out on the prototype, all that will remain to be done is design and build dust free enclosures for the cameras and light sources, enclosures that can be directly mounted to the materials handling subsystem. The actual mounting of the color imaging components to the materials handling subsystem should occur by 1 July 1991.

Approximately one year of effort has gone into determining the "best" sensors to use in conjunction with the color cameras. The analysis performed was based on difficulties that were being experienced by the computer vision subsystem in accurately and reliably locating and identifying various defects. It was clear that one of the primary problems being experienced involved accurately locating and identifying knots. Since knots are one of the most common defects, it was clear that something was going to have to be done to improve this aspect of machine vision system performance.

Another study being conducted at Virginia Tech involves the use of computer tomography (CT) image data to automatically locate and identify internal defects in logs. Data used in this research activity consists of successive scans of a number of log sections. These data have been used to simulate what x-ray images of boards cut from these sections would look like. These data clearly show that x-rays can be used to easily detect the presence of knots in boards.

Hence, an additional scanner that is being considered for use on the machine vision system is an x-ray scanner. The scanner under consideration is similar to, but has a higher spatial resolution than, the x-ray scanners used to scan luggage at airports. The x-ray scanning system under consideration has a 20 pixels per inch cress board resolution and, at 2 linear feet per second, will allow a 10 pixels per inch down board resolution. During the month of January 1991 studies will be conducted, again using CT image data, to conclusively determine whether this x-ray system will be used on the prototype. As of this writing it is believed that this represents the “best” method for detecting knots. However, the studies performed in January will be the final determining factor. Efforts are currently underway to locate sources of funding so that this system can be purchased. It will take approximately one year to integrate this device into the machine vision system. The integration involves designing and building mounting hardware so that this scanner can be attached to the materials handling subsystem. It also involves designing and building a high speed interface to the PS/2 computer. The development of computer vision algorithms to analyze the data from this scanner will proceed in parallel with the hardware development activity.

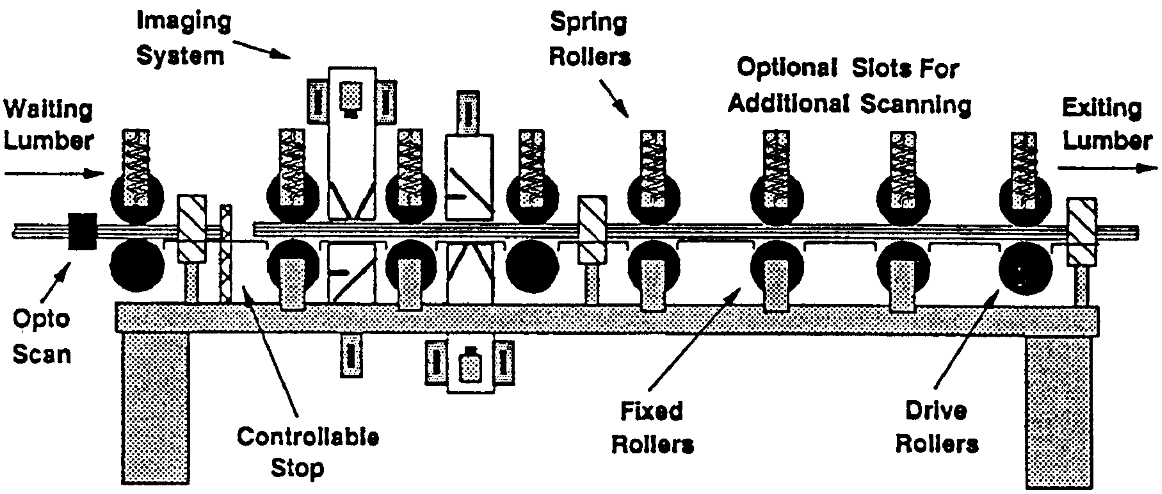
An additional scanning system that will definitely be used in the machine vision system is the new scanner being designed and built at Virginia Tech. This system uses lasers and solid state cameras to determine board thickness. The system being developed is similar to laser systems used in edging and trimming applications for locating wane. However, this system is going to have much higher resolution, having 32 pixels per inch cross board resolution and 16 pixels per inch down board resolution. Theoretically, this system could detect thickness to approximately 0.01 of an inch. An important part of the design of this system involves creating the special purpose hardware needed to collect the “range” data from this scanning system in real-time. It will take approximately 1 1/2 years to completely develop this system. Funds to procure all the necessary hardware have been raised. Funds to support the personnel costs are currently being pursued. As in the case of the x-ray scanner, the development of computer vision algorithms to analyze data from this imaging system will proceed in parallel with the hardware development activity.

### *Materials Handling Subsystem*

The materials handling subsystem has been designed and is currently being built by Automated Lumber Handling (ALH) Company of Lenoir, North Carolina. The materials handling subsystem should be built, tested, and installed on the Virginia Tech campus by 1 March 1991. An early conceptualization of this subsystem is shown in Figure 6. This conceptualization looks very much like the subsystem that has been designed by ALH. There are only two real major differences between this conceptualization and the actual subsystem. One is that the actual subsystem will use pneumatic pinch-rollers instead of the string loaded ones shown in the figure. The other is that the actual subsystem will have an optical sensor to detect board presence on one side of each of the pinch-rollers. These devices will be used to detect the presence of a board and to signal when a pair of rollers comprising pinch-roller configuration should be pressed together.

The materials handling equipment was designed to handle all hardwood and softwood lumber species of economic significance for the wood furniture, fixture and cabinet industries. The maximum dimension of each piece of lumber to be handled is 17 feet in length, 20 inches wide and 2 1/4 inches thick. The system will handle warped boards, in particular, crooked boards that fit into the 17 feet long by 20 inches wide by 2 1/4 inches thick volume. The weight per unit volume used to design the system was 6 pounds per board foot.

Figure 6




The motion control system used in the materials handling equipment has two modes of operation. The first is a constant velocity mode where a board is accelerated from a standing start to a software selectable speed before the leading edge of the board enters the first imaging station. The program selectable speeds range from 0 to 4 linear feet per second. The board is to travel through all the imaging stations at this speed. It is extremely important that this speed be accurately controlled so that high quality images can be obtained. The accuracy requirement for the constant velocity mode is that the board always be within ± 1/100 of an inch of where it is supposed to be. After the trailing edge of a board has passed the last imaging station, the board will be decelerated to a complete stop.

The design specifications for the material handling equipment required that it provide space for at least five imaging stations. The actual materials handling subsystem provides room for six imaging stations. These imaging stations are the positions where the color cameras, x-ray scanner, and the new “range” scanning device will be located.

The second mode of operation for the motion control equipment involves a start/stop type of operation where a board is moved some software selectable distance and then completely stopped. The minimum incremental distance the system was designed to handle is 1/128 of an inch. Positioning accuracy during this type of movement must also be very accurate. It was specified that the positioning accuracy must be such that the accumulated error along a 17 feet long board is less than 1/256 of an inch. ALH believes their design will be able to meet all the design requirements with the possible exception of this last specification.

The motion control equipment will be programmable in G-code. Outputs from all "important" sensing devices associated with the material handling system will be such that they can be made available to the computer system that will run the whole machine vision system.

It is very important that board vibration be minimized while a board is in an imaging area of each scanning device. It was specified that board vibration should be less than 1/128 of an inch for at least 90 percent of the system operating time. This is the reason pinch-rollers surround each imaging station.

The ALH design specifies that the materials handling equipment will be approximately 45 feet long. It will be composed of three sections, a 15 feet long materials infeed section, a 15 feet long imaging section, i.e., the section depicted in the figure, and a 15 feet long outfeed section. The system will be four feet wide. Boards will travel through the system approximately 42 inches off the floor.

Compared to other materials handling equipment being used in the forest products industry, the requirements placed on this materials handling system are extremely precise. It is about as accurate as any system handling lumber can reasonably be. Obviously, this precision does not come without some cost associated with it.

Is all this precision needed? This precision will probably not be needed on a commercially viable machine vision system. One of the purposes of this research is to find whether this precision is needed.

***Computing System***

At the spatial resolutions currently being used, a 16 feet long hardwood board will generate 32 megabytes of color image data, image data from both sides of the board. At industrial speeds this data must be collected in 4 to 8 seconds. This data must also be processed in 4 to 8 seconds. The other imaging systems will add even more data, albeit only about 4 megabytes, to this total. This additional data that must be collected and processed in 4 to 8 seconds. To many, including the authors, the above represent staggering processing requirements. Obviously, reduced spatial resolutions can and probably will reduce the required computational load, but still, one must be concerned about the cost of a computer system capable of processing this quantity of data in the above stated times. High speed computers cost more than low speed ones, usually significantly more. One must even be concerned about the cost of the main memory needed to store all this data. Real-time processing will not allow the use of disk storage. Hence, the original image data from all the scanners must be put in main memory. Intermediate data structures used by the computer vision software must also be stored in main memory. This means that there must be lots of main memory. Again there must be a concern about total system cost. High speed computer and memory cost money.

To help alleviate fears about costs, some important points need to be made. Today's bench mark processor is Intel's 486 microcomputer. The fastest 486 on the market today runs at a clock speed of 33 megahertz and can execute, and this is the important statistic, 27 million instructions per second (MIPS). The people at Intel estimate that a benchmark processor in the year 2000 will run at clock speeds of 250 megahertz and be able to execute, and again this is the important statistic, 2 billion instructions per second, i.e., 2,000 MIPS. While this projection might seem rosy, the decade of the 1980s saw an increase in speed comparable to Intel's projection for the decade of the 1990s. Interestingly, the pace of technological improvement is increasing all the time. Hence Intel's projections may be conservative. If Intel's projections are true, a relatively low cost high speed system that can meet the processing requirements posed by this problem should be available within a few years, most certainly well before the year 2000.

As to the cost of memory, another statistic is of interest. In the 1980s average memory costs steadily declined while the amount of memory available on a single chip soared. Entering the 1980s one could get either 16 kilobit or 64 kilobit memory chips. Today one can get 4 million bits on one memory chip. Also in the 1980s the cost of a memory chip declined markedly from one year to the next. A chip that cost $1.00 one year could easily cost only 60¢ the next year. Given the worldwide competition it is doubtful that any of these trends will end. This also suggests that an affordable computer system capable of meeting all the processing requirements should be available within a very few years.

With the cost of computers and memory continuing to decline, the most economical way to proceed with this research activity is to get a minimal computer system, one that will allow proof of the concept of an automatic grading system to be demonstrated. To establish proof of concept seemingly requires the collection of all needed image data at industrial speeds, the processing of this data to locate and identify grading defects in a "reasonable" time period, albeit not real-time, and the ability to create large image data bases of board images for algorithm testing and performance evaluation.

Starting with main memory, collecting image data at industrial speeds requires at least enough main memory to hold all image data generated by the various scanners. A 16 feet long board will generate approximately 37 megabytes of data from all the scanning systems. If one wants to process this data at reasonable speeds then the original data together with the data generated during processing must all be stored in main memory. This should require no more than 20 additional megabytes. Finally, processing programs and the operations system also have to reside in main memory. This should take no more than 7 megabytes. Hence, a minimal memory configuration for establishing the proof of concept is 64 megabytes of main memory. To provide a reasonable turnaround for the processing of image data, a computer is needed in the 100 MIPS range. This is a fast microprocessor based system by today's standards but systems of this speed are coming on the market. The computer vision subsystem has been designed in such a way that it can effectively use a multiple instruction stream, multiple data stream (MIMD) computer architecture. Further, the algorithms are such that a fully symmetrical parallel processing system is not needed. Fortunately, "economical" 100 MIPS machines are just now coming on the market. These systems have a MIMD architecture and are, at least currently, asymmetrical in their parallel processing capabilities. The asymmetric nature of the parallel processing is not caused by any limitations of the hardware, but rather is caused by the nature of currently available operating systems. These operating systems do not as yet support full symmetric parallel processing.

NCR will start marketing a system in the spring of 1991 that will have a MIMD architecture which can have up to four 50 megahertz 486 processors in it. With all four processors installed this system will execute approximately 160 MIPS. This system is an ideal choice for the full scale prototype for a number of reasons. First, it has the speed range that is desired. One can start with a system with only one processor in it and then incrementally add processors as needed. Hence, one can minimize one's initial investment while providing a powerful upgrade path. Next, this computer supports up to 256 megabytes of main memory, far more than the 64 megabytes required for proof of concept demonstration. Thirdly, and very importantly, this system has a microchannel input/output (I/O) bus. The high speed interface that has been designed for connecting the color camera systems to a computer is an interface that uses the microchannel. Choosing a computer with a microchannel means that this interface will not have to be redesigned. Also, the experience that has been gained in designing this interface should make designing other interfaces to microchannel bus easier than having to go to another bus structure. Lastly, the NCR machine uses a dual ported memory. Both the microchannel and the CPUS have access to memory simultaneously. Dual ported memory is precisely the type of memory the authors feel should be used in a commercial version of the vision technology being created.

## Summary and Conclusions

This paper has presented the progress that has been made on developing both the hardware and software components of a machine vision system prototype that can be used to establish proof of concept of the automatic grading of hardwood lumber. The prototype that is being developed represents an experimental tool that has many uses for forest products related machine vision development. It provides a mechanism for collecting data on full sized boards, the kind of boards that are routinely processed by hardwood sawmillers, secondary remanufactures, etc. It provides a mechanism for creating large image databases, databases that can be used to establish algorithm robustness. These same data bases can be used to quantitatively determine how well a typical employee performs various tasks in the forest products manufacturing industry. This data on human performance levels is very critical in making informed design decisions regarding the structure of commercially viable machine vision systems. This prototype provides a vehicle for studying problems of reliability and maintainability of the various hardware components, issues that should be of concern to anyone who intends to implement a machine vision system. Finally, in its most sophisticated form, after all the needed algorithms have been developed and reasonable processing speeds are possible, this prototype will provide a vehicle for demonstrating the savings a commercial machine vision system will provide the sawmiller and other forest products related manufacturers. What makes this system so important is that it provides a vehicle for investigating a number of forest products related inspection problems. Its development is not going to be inexpensive. But the utility it offers, the data it will collect, and the testbed it provides would seem to justify the cost.

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