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Automated Grading of Rough Hardwood Lumber

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Abstract

Any automatic hardwood grading system must have two components. The first of these is a computer vision system for locating and identifying defects on rough lumher. The second is a system for automatically grading boards based on the output of the computer vision system. This paper presents research results aimed at developing the first of these components. The challenge is to create robust methods that are species indepenedent and that are computationally simple enough to allow real-time processing. This paper will describe the necessary components for such a vision system and will present research results showing the progress that has been made o n each of these components.

Introduction

Any automatic grading system must have two components. The first of these is a computer vision system for locating and identifying defects on rough lumber. The second is a system for automatically grading lumber based on the output of the vision system. Significant progress has already been made on creating the second of these components [1,2].

The component that is the most difficult to design and is taking the longest to develop is the computer vision system. 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 species. But hardwood species vary significantly in their appearance and in the way undesirable features manifest themselves. Further, for an automatic system to be industrially useful would seemingly require 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. Hence off-the-shell computer vision systems cannot be used to solve this problem. Special purpose methods must be used instead.

This paper reports research aimed at developing these special purpose methods. It will show some of the processing results that have been obtained thus far and will discuss the future directions for this research activity.

The Rough Lumber Problem

The computer analysis of images of rough lumber is arguably more complex than the computer analysis of images of surfaced lumber. First there is the problem of surface moisture. Theoretically, lumber can be graded right after it is first sawn to a time 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 [3].

Next there is the variability in the exposure to ultra-violent 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 a significant 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].

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

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 assure that a particular spot on a board is not just dirt that can be scraped off but a real grading defect that is present in the board. A computer vision system will not have access to a knife.

Even the drying process introduces potential color variations in the material. Sap can come out of the material 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 digitize an image of the board can cast shadows. These shadows could be misinterpreted by a computer vision system. It is also known that the extent of surface roughness can affect the color of the material [5].

All of the above mentioned problems represent surface discolorations that can be removed by planing the material. Thus a vision system for inspecting surfaced lumber need not cope with any of these variations. Therefore the design of vision a system for examining surfaced material should be easier.

Problem Statement

For these initial investigations it was decided not to consider the problem in its broadest sense but to reduce the complexity somewhat. A decision was made to initially concentrate on three species, red oak, cherry, and poplar. Finally only fairly clear boards were selected for the study. Examples of the type of material considered are given in the figures appearing in the Results section of this paper. These figures will be discussed in detail in that section.

The boards selected were digitized using a solid state camera at a resolution of 512x480. 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 parameters means that each species will not be "optimally" imaged just 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 will 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 a scanner setting that allows all hardwood species to be imaged. This scanner setting 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 and to scan the board at regular time intervals after the surface was moistened.

The Segmentation System

Just as in the case of the computer analysis of surfaced lumber. the real-time implementation of a rough lumber vision system requires that attempts be made to reduce the computational complexity of the problem. And just as in the case of the surfaced lumber problem, the same basic methods for reducing the complexity can be tried [6-8]. If these simplification methods are used then the resulting vision system must have two components, 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.

Approximately two years of effort have gone into developing robust methods for performing the segmentation operation though admittedly the thrust of these efforts was the segmentation of surfaced lumber. The general methods used are described in References 7 and 9. 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. 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 Recognition System

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 [10]. 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 [11-13]. 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 [10], e.g., images of rough lumber.

A second class of scene analysis strategies are the top-down methods. The basis 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.

Because no image derived information is used in formulating working hypotheses top-down methods are very limited in their generality [10]. However, these approaches have been successfully used on very complicated albeit highly structured real world scenes, e.g., the analysis of chest radiographs [14].

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. To see that human vision does indeed employ a version of top-down processing consider Figure 1. At first glance this figure appears to be made up of little more than a bunch of black dots. However if one is told that a dog is present in the scene one can almost immediately spot the dalmatian. The working hypothesis "dog" leads to the application of operators that bring order to what was at first a collect of seemingly random black dots.

The Recognition System being developed for the rough lumber inspection problem uses the 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.

Figure 1. Random Black Dots or Something Else?

As of this writing the Recognition System is not completely developed. It has only been trained to identify splits/checks, knots, holes, wane, burl, heartwood, and sapwood. Also, the system does not contain all the required top-down components. It does contain a significant amount of the required bottom-up processing.

The results of applying this Recognition System to the rough lumber data described above will be presented in the next section. Hopefully the discussion of the results will help clarify the concepts of top-down, bottom-up, and combination types of processing.

Note that Reference 8 describes an earlier Recognition System, one that was designed to work on surfaced lumber. The system described in this paper differs significantly from the one in Reference 8 both in its level of sophistication, its level of robustness, and its level of completion.

Results

The analysis of the moistened red oak samples confirmed the results given in Reference 3. 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 a 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 easier and with greater accuracy if board surfaces are allowed to dry [9]

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. Dimensionally 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. However, it is believed that these techniques work well enough to be used in an industrially useful system [9].

Further 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 obtaining species independent processing [9].

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 the 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 [9].

The most important results to be presented are those obtained by applying the partially developed Recognition System to the rough lumber data. Consider the board image shown in Figure 2. This is a black and white version of the color image used in the actual processing. This image is of a rough poplar sample. Figure 3 shows the results of applying the Segmentation System to this image. As of 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 this 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 uniformly colored regions. 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.

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 more pixels of this class than any other class. This follows from the fact that the largest portion of any board is typically clear wood area whether that 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 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 4. 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

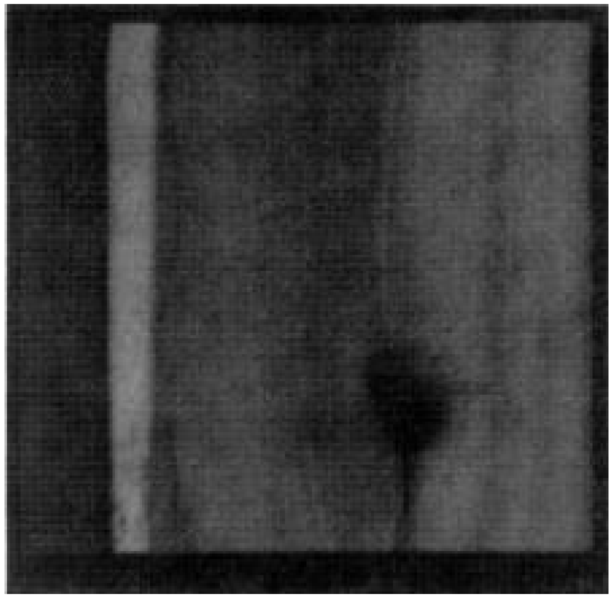

Figure 2. A Digital Image of a Rough Poplar Sample

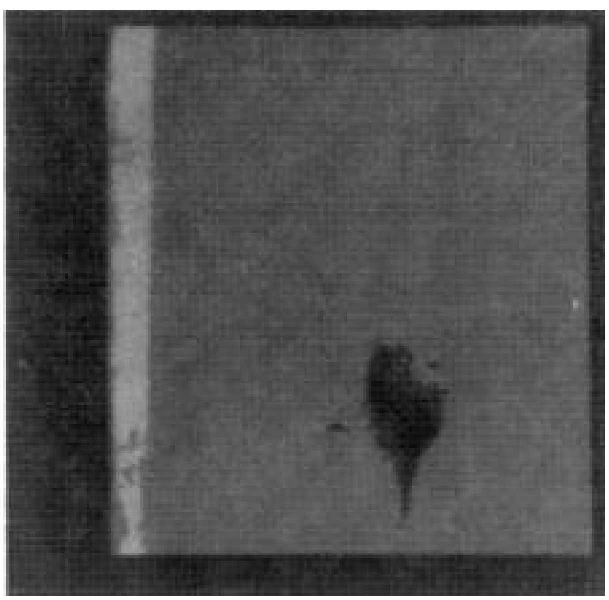

Figure 3. The Results of Applying the Segmentation System

Figure 4. Boundaries of the Connected Regions of the Segmented Image

result of this new processing is to make explicit to the computer the number and location of the connected regions. Another result of this processing is the creation of a region attribute table.

An examination of Figure 4 shows that the Segmentation System did produce some erroneous results. Most of the "noise" in the segmentation system is confined to small connected regions. Hence the next operation performed by the system is to merge these small regions with larger ones. A small region is merged with a larger one if both have similar properties. As regions are merged the attribute table is updated. A region that is merged with a larger region has its entry from the attribute table removed. The larger region of the merged pair is assigned new attributes reflecting the new properties it has derived from the smaller region. Figure 5 shows the outlines of the connected regions resulting from the merging operation.

The next processing step is again a bottom-up one. Each region in Figure 5 is first given a label based solely on its color properties. Next a relaxation type of operation [15,16] is performed to iteratively change these initial labels into ones that are "consistent" based on the conditions specified in the relaxation operation. These consistency rules include information such as the fact that wane is typically along the edge of a board and that if there is a defective region around a split/check the label of that region should probably be a knot. Note that many knots have checks in them.

The resulting labelling still has errors in it. For example it is difficult to incorporate region shape into the relaxation process. Hence it is possible (and indeed has occurred) for a round shaped region to be labelled as a split/check. In the one time that this occurred the round region was actually a hole.

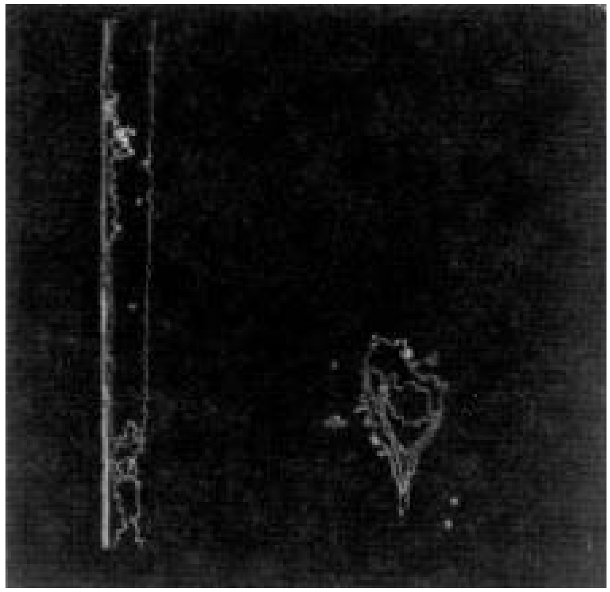

Figure 5. The Regions Resulting from the Merge Operation

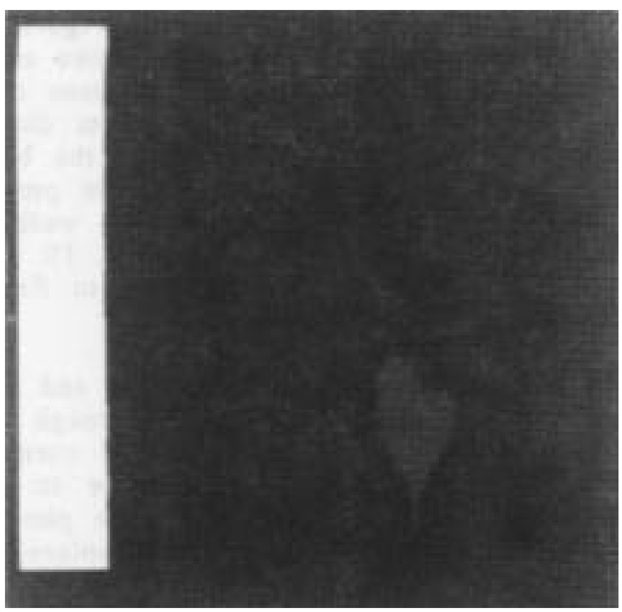

Figure 6. A Pictorial Representation of the Output from the Recognition System

To remove such errors a top-down type processing is used. For a particular region this processing uses as its working hypothesis the label that was assigned during the bottom-up processing. To understand how this processing proceeds consider the situation where a round shaped region is labelled as a split/check. Given the working hypothesis that the region really is a split/check the top-down processing would test the region shape to make sure that the shape is consistent with the labelling of split/check. Upon determining that a round shape is inconsistent with the split/check label the top-down processing would initiate additional processing in an effort to determine the true identity of the region. In this way bottom-up labellings can be checked to assure their accuracy.

The results obtained after applying the existing top-down type processing are shown in Figure 6. Note that the white area shown in the Figure 6 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 black area of the figure is the region that the Recognition System believes is clear wood, i.e., either heartwood or sapwood. The gray area in the figure is the region that the Recognition System believes is knot.

Another example of the processing results is shown in Figures 7 and 8. Figure 7 shows a black and white version of a color image of rough poplar. Figure 8 shows the results obtained from the Recognition System. White once again represents background, black clear wood, and gray knot. Note that the discoloration caused by the sticker did not affect the Recognition System.

Figures 9 and 10 show yet another processed image. Figure 9 is a black and white version of a color image of red oak. Note the saw marks and the dirt on the board. Figure 10 shows the results of the processing. The areas of white, black and gray have the same meaning as above. Note that the system did not accurately find the boundary of the knot in the upper left hand corner of the board. Finding the accurate boundaries of defects is another job for the top-down processing that is yet to be incorporated into the system. Based on the correct working hypothesis that the regions appearing in the upper left hand part of Figure 10 is a knot, top-down processing can be used to apply special purpose operators to find the exact boundary of the knot from which these regions have their origin.

The final example to be presented is shown in Figures 11 and 12. Figure 11 is a black and white version of a color image of a sample of rough cherry. The processing results shown in Figure 12 indicate that the wane was correctly found and that the sapwood and heartwood were correctly merged together to form the area of clear wood. While it is not obvious in this black and white photograph, the gray colored region representing wane is different from the gray colored region of hole. The system did correctly label this region as hole. Above the hole are some small regions that were incorrectly labelled as knot by the Recognition System. It is believed that by incorporating more top-down components into the system such errors can be eliminated.

Conclusions

The results obtained from the study suggest that developing a vision system for the grading of rough hardwood lumber is possible. All current work points to the fact that species independent processing methods can be developed. However, as encour

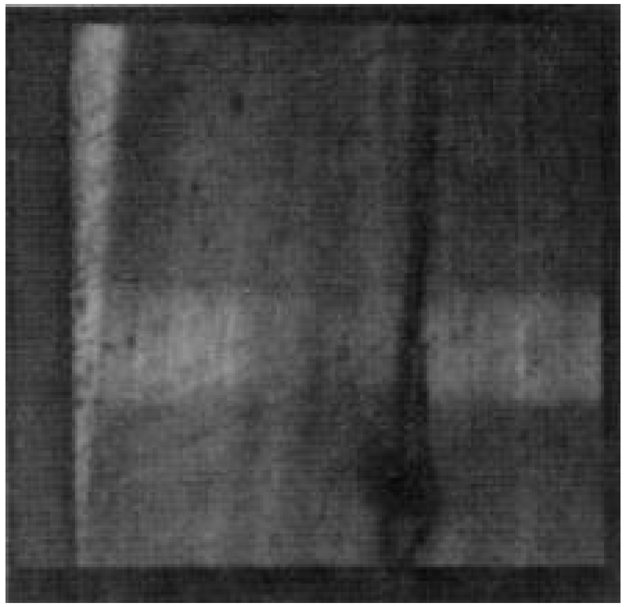

Figure 7. A Digital Image of Another Rough Poplar Sample

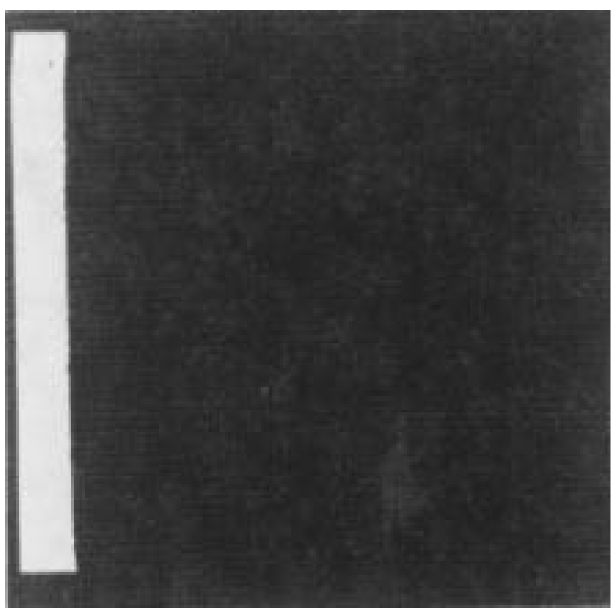

Figure 8. The Results Obtained from the Vision System

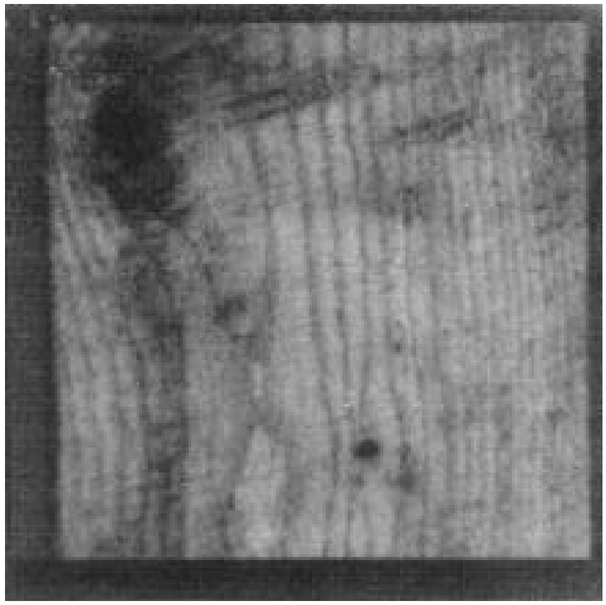

Figure 9. A Digital Image of a Rough Red Oak Sample

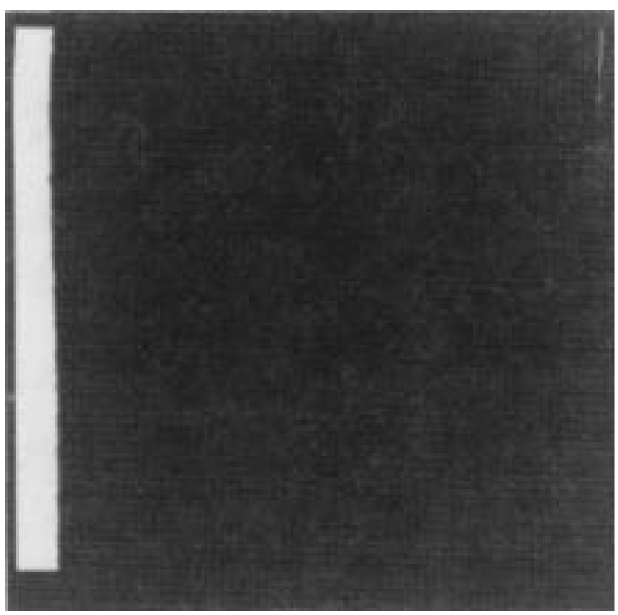

Figure 10. The Results Obtained from the Vision System

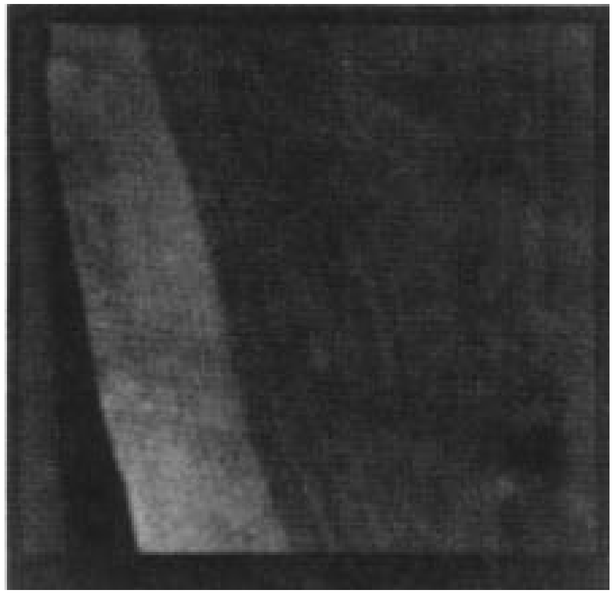

Figure 11. A Digital Image of a Rough Cherry Sample

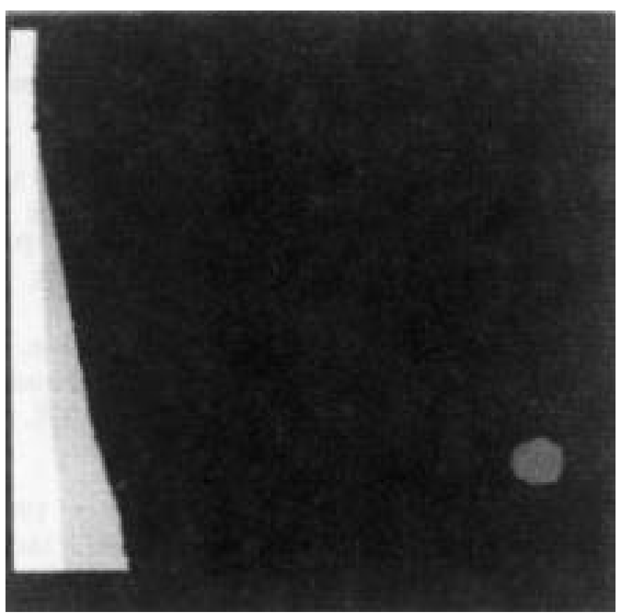

Figure 12. The Results Obtained by the Vision System

aging as these results are much further work is still necessary.

To provide a vehicle for continuing this work a prototype system is currently being developed at Virginia Tech. This system will allow the collection of image data from full 16 foot long boards. It will allow the creation of a significant image data from data base consisting of a number of hardwood species. This data base represents the next step in the creation of image processing methods for the analysis of rough lumber.

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