

A COMPUTER VISION SYSTEM FOR ANALYZING IMAGES OF ROUGH HARDWOOD LUMBER

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Abstract

A sawmill cuts logs into lumber and sells this lumber to secondary remanufacturers. The price a sawmiller can charge for lumber is dependent on its grade. In some species the cost of lumber will double in moving from one grade to the next higher grade. While the grade of a board largely depends on the distribution of defects on its surface, the grade of a board can usually be increased by appropriate edging and trimming. Optimal edging and trimming can markedly increase sawmill profits. In this paper research aimed at creating a computer vision system to power such an optimal edging and trimming system will be described. This system is designed to analyze images of rough hardwood lumber in a species independent manner. Results are presented that demonstrate the capabilities of the current system.

1. Introduction

Sawmills saw logs into boards. They sell these boards to secondary remanufacturers who use this raw material to manufacture goods such as furniture, cabinets, etc. The price a sawmiller can charge for a volume of lumber depends on its grade. In some species the price of a given volume of material can double in going from one grade to the next higher grade. While the grade of a board does to a large extent depend on the distribution of defects on its surface, appropriate edging and trimming can increase the grade of a board. Hence optimal edging and trimming provide a mechanism for a sawmiller to increase his profits.

The research reported in this paper is aimed at developing a computer vision system that can be used in an automatic edger and trimmer for hardwood lumber, an edger and trimmer that will optimize the value of the hardwood boards processed. The purpose of this computer vision system is to locate and identify defects that affect the grade of the material. The vision system must be able to detect these defects in a variety of different species. It must be able to cope with the intra as well as the inter species variations in the way these defects manifest themselves.

While some [1],[2],[3] have reported progress on developing computer vision systems for surfaced lumber, little if any work has been done on the rough lumber problem. The reason for that is that rough lumber processing is arguably more complex than the surfaced lumber problem. One of the primary difficulties is the rough board surface itself. Surface roughness is attributed to both the fibrous nature of wood and vibrations of saw blades. The structures comprising rough surface can and do cause shadows that must be dealt with by the computer vision system. Other difficulties include color changes that occur during the drying process, discolorations that occur due to exposure to

ultra-violet light, and finally, chemical secretions that occur after boards are cut from a log.

The system reported consists of three modules: a low-level module, a mid-level module, and a high-level module. The low-level module is a segmentation module that segments an input board image using a histogram based thresholding method. The mid-level module eliminates small noise regions, merges "similar" adjacent regions, and computes region properties of merged regions. The high-level module identifies the defect present in each of the regions passed to it using a rule-based approach.

2. The Low-Level Module

This module performs two functions. First it separates pixels of background from pixels of board. This is facilitated by the fact one can control the color of the background. Details of this step are given in [1]. Second, it separates pixels of clear wood from pixels that might be of a defect. To do that, a histogram based thresholding is used. While many thresholding techniques have been reported in the literature [4], most of these deal with bilevel thresholding using a single threshold. Unfortunately, gray level histograms of rough lumber are often multimodal. Using only a single threshold destroys the information about the multimodal characteristics of the image data. Hence the thresholding method used involves setting multiple thresholds based on both valley points and inflexion points of the gray level histogram. Inflexion points are examined as candidates for thresholds because small defects frequently embed themselves in the clearwood peak without forming a peak of their own.

The steps used to perform this segmentation are given below.

Step 1. Construct a gray level histogram using only black and white information derived from the color pixels of the board. Let $Hist(k)$ denote the value of the histogram at gray level k .

Step 2. Choose conspicuous valley points in the histogram as thresholds, t_1, t_2, \dots , and t_n .

Step 3. To find possible smaller defects that might embed themselves in the clear wood peak, let t_0 be the minimum gray level and t_{i+1} be the maximum gray level in the histogram. Find the interval $[t_i, t_{i+1}]$ within which the largest peak exists. This peak will always be the clear wood peak.

Step 4. Perform a Gaussian smoothing [5] to the histogram in the interval $[t_i, t_{i+1}]$. (The standard deviation of the Gaussian filter used is equal to 3.) This is needed to avoid spurious inflexion points in the histogram.

Step 5. Find the subinterval $[t_i, t_{i+1}]$, of $[t_i, t_{i+1}]$ such that $Hist(k) \geq CMIN$ for all $k \in [t_i, t_{i+1}]$. $CMIN$ is equal to 3 percent of the largest value of $Hist(\cdot)$. The reason for choosing the subinterval is because when Gaussian smoothing is applied to intervals where the values of $Hist(\cdot)$ are small typically it gives many spurious inflexion points.

Step 6. If $t_j > t_j + \text{MIND}$ select t_j as a threshold. MIND is a parameter which controls the minimum distance between consecutive thresholds.

Step 7. For each p in the subinterval $[t_j, t_{j+1}]$ determine if (a) the first derivative of the smoothed histogram at p is positive and the second derivative of the smoothed histogram changes from negative to positive or if (b) the first derivative of the smoothed histogram at p is negative and the second derivative of the smoothed histogram changes from positive to negative. If either of the above is true, p is selected as a threshold.

With regard to Step 7, it should be noted that even with the Gaussian smoothing the second derivative is frequently noisy. To prevent this noise from adversely affecting inflexion point determination, an interval about p is used to determine the sign change of the second derivative. A voting scheme is applied to each side of the interval to determine the sign of the second derivative. Experimentation has shown this to be an effective way to reduce the affect of noise on inflexion point determination.

Once the thresholds have been found, regions formed by each pair of thresholds are marked. All pixels having gray level value between two consecutive thresholds are marked the same.

3. The Mid-Level Module

This module performs several functions. The first function it performs is connected component labeling [5]. All connected regions are found and each such region is given a unique label to differentiate it from the rest of the connected regions.

Usually, the initial segmentation will produce many small meaningless regions some of which are the result of shadows being cast by the structures on the rough board surface. A second task performed by the mid-level module is to remove these small meaningless regions from any further consideration. This small region elimination is done similarly as that discussed in [6].

After all the small regions have been eliminated, the mid-level module performs further merging. This merging operation is based on a statistical T-test for equality of average gray levels between adjacent regions R_i and R_j . The underlying assumptions associated with the use of the T-test is that the gray levels of the pixels in both R_i and R_j are independent, that they have identically distributed normal distributions, and that the variances of the distributions are unknown but equal. The steps associated with using the T-test are given in detail in [7]. Similar statistical tests have been used by other investigators, for example, [8].

After the region merging operation is complete, a vector of features is extracted from each of the resulting regions. These features are : area, average gray level, center of mass, minimum bounding rectangle, elongatedness, perimeter, compactness, and flag_board_boundary (a flag indicating whether a region is touching board boundary or not).

4. The High-Level Module

This high-level module's function is to perform the scene analysis task, i.e., to identify the defect present in each of regions passed to it from mid-level module. Currently, this module has been taught to recognize four of the most common defect types. These are knots, holes, wane, and splits/checks. This module uses a three step process to perform the scene analysis task.

First, based on the region properties computed by the mid-level module, each region is assigned a vector of initial

confidences. Each component of this vector is the confidence that the region is of a particular defect type. The evaluation of these confidences is based on fuzzy set theory [9]. (Details of this confidence calculation are shown later.)

Once all the regions have had their initial confidence vectors computed, defect detection procedures are applied. (All the regions are initially "unlabeled".) These defect detection procedures are very specialized. Each defect detection procedure is designed to detect a particular defect. The basic strategy used in each defect detection procedure is to first consider regions that seemingly represent "exemplary" examples of the defect the procedure was designed to recognize. Specialized defect detection methods are applied to these regions. A region is considered to be an exemplary example of a particular defect if this region's initial confidence vector has a high value for the component that corresponds to this defect type. After all of the exemplary regions have been processed, regions representing more "ambiguous" examples of that defect type are considered by the defect detection procedure. The labeling of these regions is based on defect detection methods that gauge contextual dependency and similarity of properties. (One procedure for detecting splits/checks is described later in detail. Other defect detection procedures are constructed in a similar fashion; see [7] for details.)

The recognition process is ordered. The procedure for identifying split/check is applied first. The procedure for identifying holes is applied second. The procedure for identifying wane is applied next. The procedure for identifying knots is applied last.

Even after all the defect detection procedures have been applied, there may still exist unlabeled regions. Such regions are labeled using spatial contextual dependency. First, every unlabeled region is labeled as clear wood. Next, if any unlabeled region is completely enclosed by regions labeled as defects, then it is given the same label as the region with which it shares the longest common boundary.

The final step of the recognition process is a labeling verification step. This step is necessitated by the fact that even after region merging, each region does not usually correspond to a defect; typically a defect is fragmented into several regions. In this step, groups of connected regions that have the same label are combined to form a single new region that is added to list of existing regions. As each of these regions is formed, measures are extracted. These measures are used to verify the common label of small regions comprising the new region.

Initial Confidence Calculation

To use fuzzy set theory to assign initial confidences requires that a high-level qualitative description of each defect type exist. Each defect type is described using some primitive terms. For each of these terms, a membership function is defined. For example, splits/checks are characterized as "long" and "dark" defects. The fuzzy membership function for "long" is defined by

$$\mu_{\text{long}}(x) = 0, \quad x < t_1,$$

$$= \frac{t_1 - x}{t_1 - t_2}, \quad t_1 \leq x \leq t_2,$$

$$= 1, \quad x > t_2$$

where x is the area of the current region, and where t_1, t_2 are parameters determined empirically.

Based on these membership functions the confidence vector

for each region can be computed using intersection and union operations on fuzzy sets. For example, let $cf(R, spchk)$ be the confidence that region R is a split/check. Then, $cf(R, spchk)$ is calculated using

$$cf(R, spchk) = \min(\mu_{\text{long}}(x), \mu_{\text{dark}}(y))$$

where x is the elongatedness of region R and y is the average gray level of region R.

Split/Check Detection Procedure

Exemplary regions, ones having high split/check confidence (>0.5), are considered in the order of the average gray level, i.e., the darkest region is considered first. Let R be such an unlabeled region. If R does not have any adjacent region that has been previously labeled as a split/check and if R is much darker than its adjacent regions, then R is labeled as a split/check.

For regions that are not exemplary, a rule is used to determine whether any of these regions should be labeled as a split/check. Let R be such an unlabeled region. If R has some degree of confidence of being a split/check (>0.1) and if there is an adjacent region, R', that has been already assigned as a split/check and if the elongatedness of R merged with R' is greater than that of R, then R is labeled as a split/check. This rule detects regions that have low confidence of being a split/check but are aligned with a region already recognized as being a split/check.

5. Experimental Results

Images used in this experiments were obtained by digitizing a number of rough lumber boards for several species of wood: cherry, oak, poplar, and maple. The digitized images were all created using the same camera setting and lighting condition. The images were shading corrected to minimize spatial nonuniformities in shading due to uneven illumination and nonlinearities in camera [10]. The shading corrected images that are input to the system have three 8-bit 480x512 color channels. The spatial resolution is approximately 64 points per inch. This high resolution is required in order to detect small splits/checks.

The current system has been implemented in FORTRAN 77 on a VAX 11/785 minicomputer system. Test of our system has been performed using approximately 30 boards from four different species. Two processing examples are shown to demonstrate capabilities of the current system. Each figure shown has two parts: (a) original black/white image of a board and (b) results of defect recognition. (In (b) of each figure, each defect label is given a unique gray level with its name. White area is clear wood.)

Fig. 1 for a oak board shows a small knot and a large knot containing a split/check which have been correctly identified, in spite of much "noise" in the image due to the wood grain and some dirt. Fig. 2 shows a cherry board which contains clear wood, wane, and a large hole. Notice that a wane and a hole are correctly identified, although there are some regions incorrectly labeled as knots. Those labeling errors can be corrected by a more powerful top-down defect verification scheme that is planned in the future.

6. Conclusions

A computer vision system for locating and identifying defects on rough hardwood lumber in a species independent manner has been described. While it has limited recognition capabilities, only being able to identify four defect types, it does suggest that species independent methods can be found for accomplishing the required tasks. Obviously, much further research is required. The future research should be directed toward expanding the list of defects that can be

identified as well as improving accuracy of the system. Clearly, the top-down processing in the current system needs to be augmented to help improve recognition accuracy.

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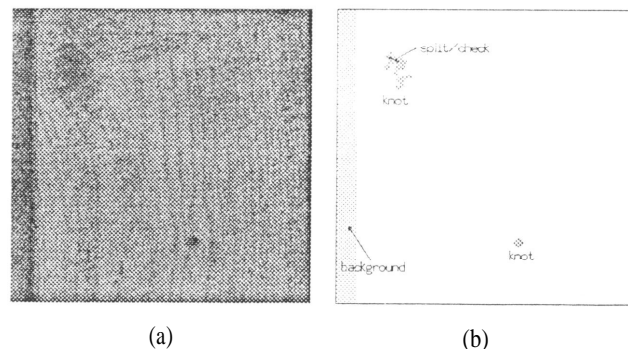


Fig. 1. A rough oak board. (a) Original image. (b) Results of defect recognition.

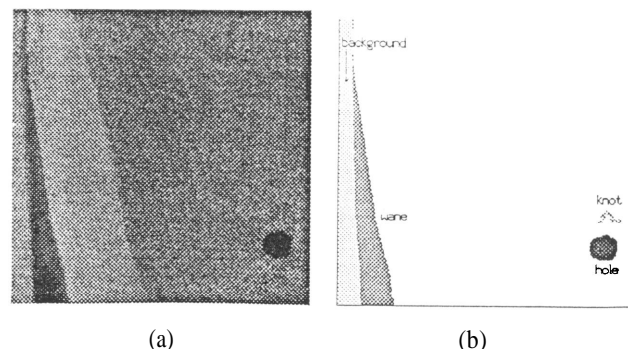


Fig.2. A rough cherry board. (a) original image. (b) Results of defect recognition.

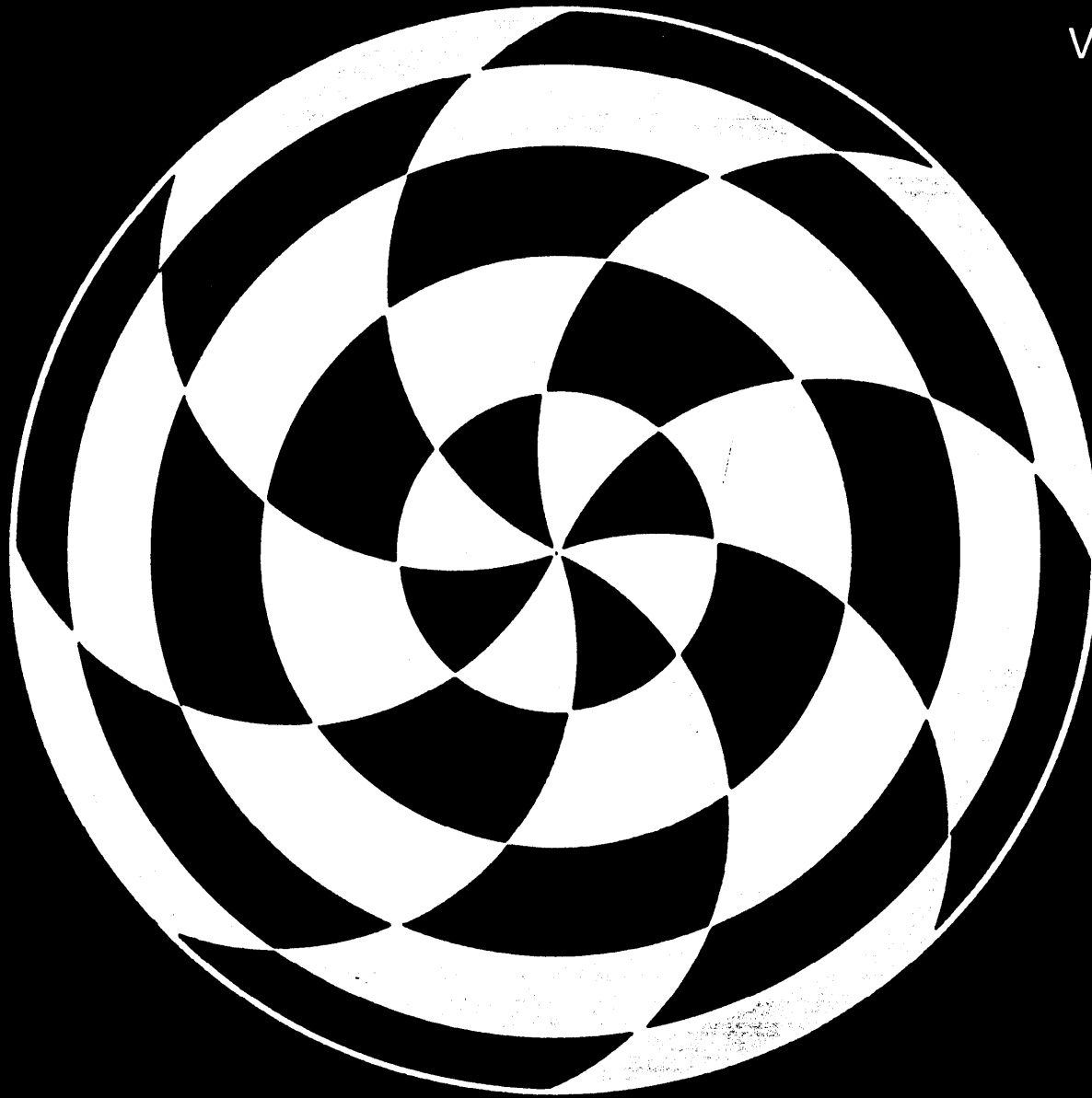
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