CT Image Sequence Analysis for Object Recognition – A Rule-Based 3-D Computer Vision System

Dongping Zhu, Richard W. Conners
The Spatial Data Analysis Laboratory
Virginia Polytechnic Institute and State University
Blacksburg, Virginia 24061-0111

Daniel L. Schmoldt, Philip A. Araman
USDA Forest Service
Southeastern Forest Experiment Station
Brooks Forest Products Center
Blacksburg, Virginia 24061-0503

Abstract - Research is now underway to create a vision system for hardwood log inspection using a knowledge-based approach. In this paper, we present rule-based, 3-d vision system for locating and identifying wood defects using topological, geometric, Statistical attributes. A number of different feaures can be derived from the 3-d input scenes. These features and evidence functions are used to compute confidence values for object membership in different defect classes. We will illustrate the use of different knowledge sources in a set of independent and concise rules.

I. Introduction

A computer vision system for automatically processing hardwood logs is intended to help the hardwood sawmill industry automate, reduce costs, and increase product volume and value recovery. A key to the success of this work is the ability to automate the detection of defects inside logs. Defects must be located, properly sized, and identified. Other computer programs are needed to grade the logs and determine the possible board cuttings from the logs.

Knowledge of log defects is critical to the primary breakdown of hardwoods. Tree-length roundwood, hauled to the mill from the forest, may need to be cut prior to further processing into lumber or veneer. With internal defect information, it becomes possible to cut roundwood so that defects are removed from the log or isolated at either end. This leaves larger areas of valuable clear wood in the log, gives it higher value. Next, a sawmill operator must decide whet her to process a log as veneer or as lumber. Logs or lengths of a log can be identified as veneer quality; utilization as veneer can increase log value by a factor of 10. In processing a sawlog, positioning of the log is important for producing boards with as much defect-free surface as possible. In recent years, several computer vision systems have been developed to inspect lumber and logs in the forest products industry [2][3][4].

A nondestructive way of inferring the internal structure of a three-dimensional object, such as a log, is to use Computerized Tomography (CT) to calculate the attenuation of each small volume of the log to x-ray transmission. CT imaging of a hardwood log along its length produces a stack of cross-sectional slices representing the three- dimensional structure of the log. The image value at each pixel is called the CT number. Because x-ray attenuation is dependent on material density, CT numbers represent density measurements of the wood structure in a log.

Our vision system consists of two basic modules: a low-level module and a high-level module. The low-level module performs the tasks of image filtering, segmentation, and region detection and merging. A 3-d labeling procedure transforms 2-d regions from segmentation into 3-d objects. The high-level module conducts defect recognition of these 3-d objects using a rule-based approach. For a more indepth presentation of the low-level module components, such as image smoothing, segmentation, and region merging, readers are referred to [7][8]. This

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paper addresses 3-d labeling, and also defect recognition using a rule-based approach. In particular, we discuss: (1) grouping connected 2-d regions on a sequence of CT slices into an integral 3-d *volume,* (2) selecting image features for the defect recognition stage, (3) computing the confidence values of a defect, (5) organizing different features into a set of independent and concise rules, and (5) applying this set of rules to the recognition problem.

II. Volume Growing by 3-D Labeling

Prior to 3-d object recognition, a sequence of CT slices need to be segmented on a slice-by-slice basis. This segmentation process produces a number of uniform regions on each image which, when grouped together, represent the 3-d information of different wood defects inside a log. Input to the 3-d labeling procedure is a sequence of segmented images generated from the segmentation component in the low-level module [7]. A 3-d version of the connected component labeling algorithm [6], called *3-d volume growing,* is adopted here to group individual 2-d regions on different slices into 3-d integral objects.

Inside a log, defects manifest themselves in varying shapes. In 3-dimensions, a knot would appear like a paraboloid, bark like a generalized cylinder, a hole like a cylinder, and a split like a ribbon, etc. To identify the proper 3-d volumes of potential defects, pixels with similar CT attributes on a number of segmented images are grouped into connected volumes, according to 6- or 18-neighborhood connectiveness in 3-d.

The 3-d volume growing algorithm that is used in the log inspection system is briefly described as follows. Let $x(i,j,k)$ denote an label assigned by the segmentation process at a point (i,j) on the kth slice from a sequence of S segmented images. When raster scanning a sequence of images, a new image label is given to each pixel of each image in the sequence. This new label is to identify the pixel as a part of a 3-d entity. Because our primary goal is to differentiate defects from clear wood and air, we need not label wood and air. For this purpose, a binarization process is adopted in which all defect pixels are marked 1 and the remaining pixels are marked 0. Let us denote the image label at the current 3-d location by p, and those at the 3 neighboring locations by a, b, and c respectively, i e., $p = x(i,j,k)$, $a = x(i,j,k-1)$, $b = x(i,j-1,k)$, and $c = x(i-1,j,k)$. Our 3-dimensional labeling algorithm can be expressed by the following algorithm:

<u>A 3-D Volume Growing Algorithm</u>

For each non-background pixel $x(i,j,k) \neq 0$:

1. if a=b=c=0, a new volume is found and assign p a new label.

2. if two of $\{a, b, c\}$ are 0, assign p to the third nonzero label.

3. if one of $\{a, b, c\}$ *is* 0, then

    3.1 if the other two neighbors have the same label, assign p to that common label.

    3.2 if these two have distinct labels, assign p to the label of one of them, MERGE(2).

4. if none of $\{a, b, c\}$ is 0, MERGE(3)

In the above algorithm, procedure MERGE(n), where *n* is an integer number, is a subroutine in which the *n* individual volumes are merged into one integral 3-dimensional entity. To facilitate this merge operation, a tree data structure is created for each object and the labels of the n volumes are stored under the same tree. In this way, all the 3-d volumes that are connected but have different labels will be merged into the same volume representing a 3-d object.

In practice, we only need to be able to detect those defects that have a significant volume. Defects smaller than a certain volume are discarded and treated like clear wood. For this purpose, an integer value is preset as a threshold for volume size against which all the labeled volumes are to be compared. Any volume of a size smaller than this threshold value is eliminated by merging it with its nearest neighboring volume or merging it with the background. This merging process usually eliminates false defects resulted from segmentation, and retains the well-connected 3-d objects as defects, such as knots, bark, splits, decays and holes. Output from this 3-d volume growing algorithm is a number of 3-d objects that are to be recognized by the high-level module discussed in the next section.

III. Rule-Based Object Recognition

Any defect type can manifest itself in many different ways. For example, knots represent a single type of defect; however, their shape, density, size, and orientation can vary greatly. Consequently, statistical or analytical classification procedures are difficult to implement successfully. Less exacting methods, therefore, may be better suited to this type of problem. A heuristic, rule-based recognition system was used by [2] to identify defects in sawn lumber. Rule-based systems are flexible in that special rules can be written to handle exceptions [1]. For these reasons, the machine vision system under study adopts a rule-based approach to perform 3-d object recognition.

A. Feature Selection

For each of the 3-d *volumes* detected by the above volume growing process, statistical, geometric, and topological features are readily computed from the 3-d image data. Currently, 5 basic features have been derived to enhance the separability of bark, knots, and clear wood. Additional features can be added to the system as other defects need to be recognized or as current defects need to be distinguished better. The following are brief descriptions of the object features that may be computed from a sequence of images:

(1) *The mean value (MEAN)*- This feature is obtained by finding the mean CT values for all pixels contained in a *volume.* Because bark and knots have higher absorption rates than clear wood, this is an important feature to identify defects.

(2) *The variance value (VAR)*- Sample variance of a volume is calculated as in the calculation of MEAN above. This is a useful feature to distinguish bark from knots because they have different variance values.

(3) *The minimum distance (DIST)*- This is taken as the distance from the centroid of a *volume* to the Z-axis. Bark (except for included bark pocket) is a great distance away from the center (Z-axis) of the log, therefore, it has a large DIST value. Clear wood is near the center of the log, and it has a small DIST. Therefore, this is a good feature to identify bark.

(4) *The predictor (TOUCH)*- This is a binary predictor with value 1 or 0. Value 1 (0) indicates a *volume* touching (not touching) the background (air). Since knots usually do not touch air, this is a good feature to differentiate knots from other objects.

(5) *The volume (VOLM)*- This is the 3-d volume occupied by an object. Clear wood has a much larger volume than any other objects in a log. Splits and holes usually have a small volume. Therefore, this is a good feature to distinguish clear wood from defects, and splits and holes from the remaining defects.

B. Computing Confidence Values

Each object has a confidence vector to describe the belief that the object belongs to each defect category. From the population distribution of a given feature, we can derive threshold values that separate the population of values for that feature into discrete classes. To properly define ranges on the feature distributions for different linguistic qualifiers, a group of threshold values are determined using a set of training data. Threshold values are visually determined by the peaks and valleys on the histograms of individual features. Linguistic qualifiers, such as "high" and "low", label these classes. An *evidence function*, expressed as a discrete or continuous step-type function, can be used to relate linguistic qualifiers and levels of evidence for various defects. Fig. 1 shows three examples of such *evidence functions* $f(v)$ for feature $v = VAR$ for the defects bark, knots, and clear wood. According to these step-type functions, a linguistic qualifier L (for Low), M (for Medium), or H (for High) is associated with ranges of values of the feature variable v. Here T1 and T2 are two thresholding values obtained from a histogram of the feature v. For each feature value computed from image data, such functions assign individual values to the confidence vector for a candidate *volume.* This is in fact a voting process where a higher vote is given to the strong evidence and a lower vote to the weak one.

C. Recognition Method

To use prior knowledge about different categories of defects to classify a candidate object, a correspondence must be established between the linguistic qualifiers and possible defect manifestations within a log. A production system or rule-based approach is adopted since it easily implements this type of reasoning. There are many ways to combine feature values and decision paradigms to make rules. Antecedent conditions could refer to the value of a single feature, the values of all the features, or the values of some subset of the features. The consequent action could make a decision on membership or non-membership in a class, or simply contribute evidence to that decision.

In our approach, a production system with simple conditions was built; each rule considers one basic feature. The action of a rule is to contribute positive evidence (1.0) to classes in which the feature is usually present, negative evidence (-1.0) to those in which it is usually absent, and no evidence (0.0) to the rest. To accommodate situations where the feature is present occasionally and absent at other times, half evidence (0.5 or -0.5) is contributed to the classes. The rules in a production system are of the following form

IF (conditions) THEN (actions).

In implementing rules, individual rules are grouped into conjunctive rules, where the action part contains several confidence value assignments. As an example, the conjunctive rule *Rule_Touch* using feature *TOUCH* is expressed as

```
Rule_Touch: vote to 3 classes by feature TOUCH

    if(touch(k)=1) then ("touching")
    cv(touch, bark) = 1.0
    cv(touch, knot) = -0.5
    cv(touch, wood) = 0.5
    else if(touch(k)=0) then ("not touching")
    cv(touch, bark) = 0.5
    cv(touch, knot) = 1.0
    cv(touch, wood) = -0.5
```

In this rule, variable touch(k) is the *TOUCH* feature value of the kth *volume*, and cv(touch, bark), cv(touch, knot), and cv(touch, wood) represent the confidence values assigned by rule *Rule-Touch* to bark, knots, and clear wood, respectively. This rule provides strong positive evidence (1.0) for bark that touches the background, whereas it provides weak negative evidence (-0.5) against a knot that touches the background.

After applying all 5 rules to a candidate *volume*, a matrix of confidence values cv(i,j), (i = 1, 2,..., 5, j = 1, 2, 3.) are generated. The *total vote* for an object, denoted by *TV(j), is* the total confidence value obtained by adding up all the confidence values assigned to the object by all 5 rules. For an expert system comprised of N_r rules, this *total vote* can be expressed as

$$TV(j) = \sum_{i=1}^{N_r} cv(i,j),$$

In our case, N_r, the number of rules, is equal to 5. The class with the highest total vote is designated as the class to which the object belongs. The next section shows some experimental results of applying these rules to CT images taken from a hardwood log.

IV. Experimental Results

The method described in this report was applied to recognize CT images taken from a hardwood log that contained bark, knots, and clear wood. The original 12-bit images were 256 x 256 with pixel resolutions *8.0mm* between slices and *2.5mm* within a slice. After 3-d smoothing, images were segmented one by one, and the connected components on all slices were grouped together to produce a number of 3-d *volumes* of unknown defect type.

A small set of CT slices were selected from a sequence of the log images as the training data. Feature distributions computed from this training set defined a set of thresholding values that were used to determine the linguistic qualifiers of the feature values. Rules were then applied to individual candidate *volumes* to assign confidence values to different defect classes. Adding up the confidence values contributed to a *volume* by all rules, the object was assigned the class that had the highest total confidence value.

Two experiments were conducted using the above approach to recognize wood defects inside a yellow poplar log. The first experiment was performed with 4 training images (slice No. 2 through slice No. 5 of log YP01). In this experiment, all defects and clear wood were correctly recognized by our 3-3 vision system. In the second experiment, a sequence of 4 images from the same log (slice No. 21 through slice No. 24 of log YP01) were used as testing samples. Threshold values that were derived in the first experiment were used as thresholds here. As in the first experiment, all classes of objects were correctly recognized. Fig. 2 to Fig. 4 show the results of processing 4 images in the first experiment. Fig. 2 shows the original CT images of these 4 slices which contain bark, knots, and clear wood. Fig. 3 demonstrates the results of image segmentation. Finally, Fig. 4 contains the results of applying the 3-d volume growing algorithm to this sequence of segmented images. On reviewing Fig. 3 and Fig. 4, it is clear that two pieces of bark and one knot have been detected, and that the clear wood and the background (air) are also correctly differentiated from the defects.

V. Summary and Discussion

In this paper we have presented a rule-based 3-d vision system for automatic log inspection using computerized tomography imagery. We have described several image features, that can be derived from the input image sequence and are capable of handling different aspects of the log defect recognition problem. We have also presented a way of computing confidence values for membership in different defect classes using the population distributions of various features. Finally we have described how 3-d object attributes can be encoded in a set of simple rules and used to recognize defects.

The main advantage of this simple system is that it is repeatable without intra- and inter-observer variability. The rules can be used in many different ways. A simple voting scheme is chosen for the vision system because the decision-making process is easily understood and debugging is simplified. However, deciding the magnitude of the vote is as difficult as determining a prior probability vector in the statistical pattern recognition method. Combining domain independent low-level image heuristics with domain-specific heuristics in a high-level module creates a very general recognition mechanism, one that can handle different wood species in automatic log inspection.

Our aim here is to demonstrate useful and flexible approach that addresses some aspects of the vision problem. As an example, we have taken CT log images and shown some image features that could be extracted and simple rules that could be formulated to obtain a conceptually feasible inspection system. Clearly, rule-based systems are problem specific. Therefore the rules presented in this paper need to be augmented and fine-tuned in order to accommodate more complicated log defects and to make the rules more robust. Nevertheless, the proposed rule-based approach to the machine vision problem seems promising; and a relatively inexpensive, accurate, and fast vision system for hardwood log inspection seems possible.

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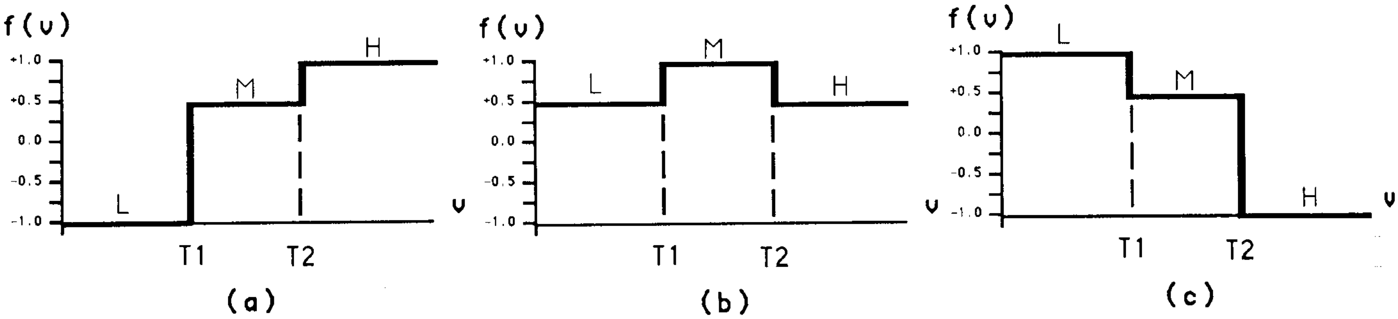

Fig. 1 An evidence function *f(v)* relates discretized values (L, M, H) for feature $v = VAR$ with evidence values for the defect bark (a). Knots (b) and clear wood (c) have different evidene functions. The threshold values, T1 and T2, were established from the distribution of *VAR* values.

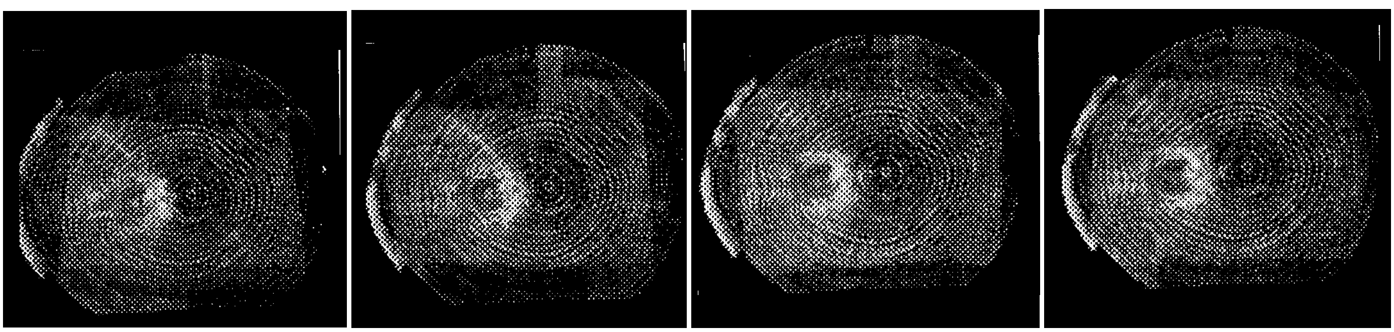

Fig. 2 (From left to right) Original CT images of slices 2, 3, 4, and 5 from a yellow poplar log.

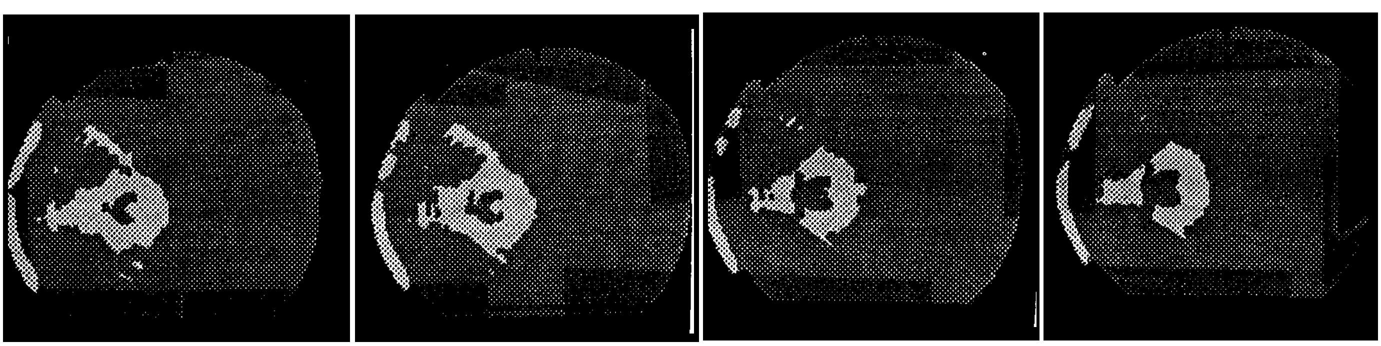

Fig. 3 Segmentation results of the images in *Fig. 2* using multi-thresholds.

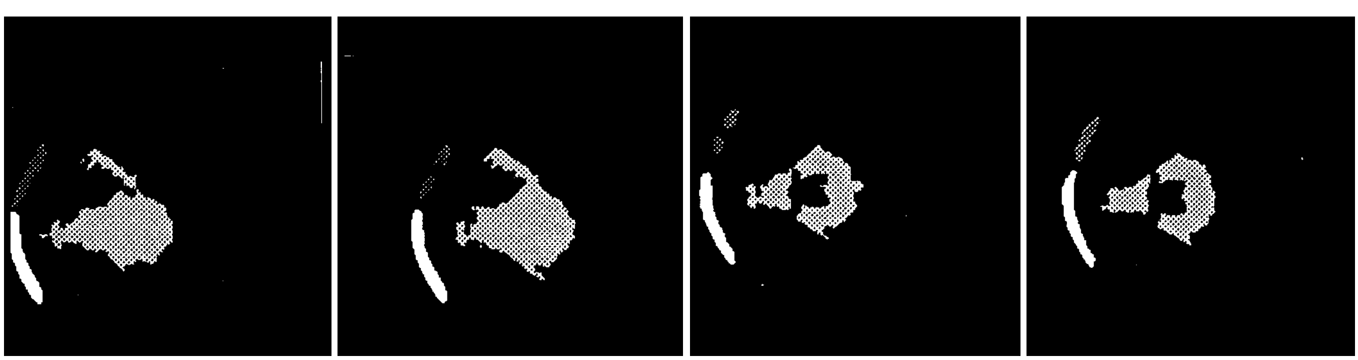

Fig. 4 Two barks and a knot detected from the image sequence in *Fig. 3* by 3-d volume growing.

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