CT Image Sequence Processing For Wood Defect Recognition

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Abstract-The research reported in this paper explores a non-destructive testing application of x-ray computed tomography (CT) in the forest products industry. This application involves a computer vision system that uses CT to locate and identify internal defects in hardwood logs. The knowledge of log defects is critical in deciding whether to veneer or to saw up a log, and how to position a log so that the boards sawn from it will have as much clear face as possible. To apply CT to these problems requires efficient and robust computer vision methods. This paper addresses one aspect of the problem of creating such a computer vision system, i.e., the issue of efficient image filtering for suppressing unwanted detail in CT log images. In particular, this paper describes an image filtering method based on a spatial adaptive least square filter. Simple in structure and efficient in computation, this filter is not based on assumptions about a signal model, but rather on a fixed filtering structure. In conjunction with image segmentation and region growing procedures, the new filter is used in the machine vision system to produce well defined regions that represent areas of potential wood defects.

Index Terms-*computed tomography, wood defects, adaptive image filtering, computer vision.*

I. Introduction

X-ray radiation passing through an object travels in a straight line, and is attenuated by the structure within the object. Some characteristics of this structure can be inferred from the way it attenuates radiation. The attenuation caused by each small volume of space that lie along the radiation's path can be represented as a linear equation whose variables represent the linear absorption of these volumes. The constant in this linear equation is the amount of radiation measured at a detector. A non-destructive way to infer the structure of an object as is characterized by x-ray attenuation is to determine the linear absorption of each of the small volumes comprising the object. If one illuminates these volumes from many different directions, recording the amount of radiation detected along many straight line paths, the result can be expressed as a set of simultaneous linear equations. If enough directions are used and enough recordings are taken the resulting set can be solved to yield the linear absorption of each small volume within the object.

The above represents the basis for x-ray computed tomography (CT). To simplify the calculations CT machines usually move the source and detector around in a plane, recording measurements at preselected locations. The simplification that results is that one need only be concerned with the small volumes that intersect the plane. This markedly reduces the number of variables in the linear equations and, hence, markedly reduces the computational complexity of the "reconstruction" process. This "slice" shows the internal structure of the object along this intersection of this object with the "imaging" plane. The first application of CT was in medicine [1]. More recently the technique has been used in other nonmedical environments such as geological prospecting for minerals [2], three-dimensional imaging with electron microscopy [3], and cross-sectional imaging for nondestructive testing [4]. The impact of CT in radiology, diagnostic medicine and non-destructive testing has been revolutionary.

The research reported in this paper explores a non-destructive testing application for CT. This application involves using CT to locate and identify internal defects in hardwood logs. There are two good reasons for wanting to locate and identify internal defects in logs. The first decision that must be made about a log is whether to saw it into lumber or to veneer it. Assuming the log is worth x dollars as a saw log, a log of the same dimension would be worth $10x$ dollars as veneer log. For example an 8 feet long walnut saw log is worth approximately $800. An 8 feet long walnut veneer log is worth $8,000. Hence it is very important that one be able to accurately decide whether a log is of high quality and, hence, should be veneered, or that it is of lower quality and should be sawn into lumber. To accurately make this decision requires information about the location and identity of internal defects within the log.

If a decision is made to saw a log into lumber, the next decision that must be made is how to buck the log, i.e., how to position it, so that the boards sawn from the log are of the highest possible grade. Studies [5] have shown that the value of lumber sawn from a log can be increased from seven up to twenty-one percent if optimum positioning is used during the saw up. The optimum positioning depends on the location and identification of internal log defects. The basic goal of the saw up is to create boards that have as much clear face as possible.

Given the current high cost of medical CT units, the economic viability of using these systems on forest products applications must be a concern. However, there is every reason to believe that the cost of CT machines will go down markedly in the future. First a significant percentage of the total cost of CT machine is the cost of the computer and special purpose hardware used to do the reconstruction. *Intel Corporation* estimates that a bench mark microprocessor in the year 2000 will be able to execute 2 billion instructions per second. If this is true the special purpose hardware and minicomputer used on today's machines will be replaced by one or more microprocessors in the future. The cost of one or more microprocessors should be significantly less than the digital hardware used in today's CT machines. Another significant cost component in today's units is the research and development (R&D) cost. A relatively high volume market, such as the one that would be associated with the forest products application, should allow R&D costs to be spread over more machines reducing this cost on a per machine basis. Finally, the spatial resolution required for either of the above forest products applications will probably be less than that required for medical diagnosis. The reduction in spatial resolution affects not only the computational complexity of the reconstruction but also the nature of the radiation source. The lower the resolution the less expensive the computational hardware and the less expensive the radiation source.

If CT is to be used to attack the above stated problems, the analysis of CT imagery is going to have to be done by computer. This paper explores one aspect of the problem of creating a computer vision system that uses CT data to locate and identify interred defects in logs. In particular, this paper addresses the issue of efficient CT image filtering for suppressing unwanted detail such as the annual rings in the CT images of hardwood logs. By incorporating the 3-dimensional correlation information among image pixels, an improved adaptive algorithm for image filtering is presented. Analysis and experiments demonstrate its superior filtering performance over some other methods.

II. Problem Background

Removing unwanted image details from images can be an essential step toward successful image interpretation. Like images in other vision system applications, hardwood log CT images contain some unwanted image details. In particular the annual ring structure tends to adversely affect the whole image analysis task. For instance, Fig.1 shows one example of the log CT image (a) and a profile image (b) demonstrating a well pronounced variation in its gray values in the horizontal direction. Without any preprocesing such as filtering or smoothing, segmentation will produce artifacts that are caused by the annual rings on the image slice. Fig.1 (d) illustrates one segmentation example of an CT image that is not filtered. Note the artifacts caused by the annual ring structure.

Therefore, an important problem in CT log image processing is how to get rid of these unwanted annual rings while preserving other important image details, e.g., the presence of small checks. The annual rings of a log comprise the high frequence signal component in the log images. Statistically, these annual rings behave like high frequence noise. The most common way of removing high frequence noise from digital images is to use filters such as a lowpass filter. Most of current image filtering or smoothing methods fall into two basic categories: (1) model-driven or optimal methods such as Wiener and Kalman filters, and (2) heuristic or adaptive methods such as the adaptive algorithms [6], median filters, and gradient inverse smoothing [7]. The model-driven methods assume a particular signal model, making their effectiveness heavily depend on the validity of a particular signal model used. The heuristic methods perform nonlinear smoothing or order-filtering in the spatial domain. Such filters are easy to implement and are typically computationally simple. Unser [8] has proposed an adaptive least-squares filtering structure for image restoration in which no assumption is made about the underlying signal model. By locally optimizing a least squares error criterion, this adaptive filter recursively computes an image estimate from a weighted sum of the observed noisy image and of the output of an initial 2-d linear restoration filter.

Several of these image filtering techniques, including the 3-σ filter, median filter, and 2-d spatial adaptive filter, have been tested on the CT log images, and the general results are not satisfactory since they all produce severe artifacts during image segmentation. Fig.2 (b) and Fig.3 (b) are the segmented images after image filtering using two such filters. In each of these segmented images, there exist artifacts in the clear wood regions.

To improve the performance of image sequence filtering, a modified version of Unser's method was developed that employs the 3-dimensional correlation information among pixels on consecutive slices in a sequence of images. Application of this modified filter structure to CT images has demonstrated that this filter gives improved performance over the other filters that have been tried. In comparison with the original 2-dimensional algorithm and other non-adaptive filtering methods, this adaptive algorithm has the advantage of better preserving spatially structured details inside an object, e.g., fine edges (like splits) and textured regions (like knots), while filtering out the unwanted detail (like annual rings) from the image. The next section will first describe the properties of Unser's filter. It will then present modifications that have been made to this filter to extend it to 3-dimensions. In the context of CT image sequence analysis, these modifications allow the spatial interdependence that exist among consecutive images to be incorporated into a 3-d linear adaptive filter. This filter requires no *a priori* knowledge of image properties. In this 3-d algorithm, the first- and second-order adjacencies of pixels are employed to capture the spatial interdependence among these points.

III. Image Filtering by A Spatial Filter

For nonlinear smoothing of digital images, Lee's adaptive filter [6] is particularly efficient. It computes a weighted sum of the noisy image and of the output of a moving averaging filter that provides an estimate of the local image average value. However, this approach assumes that the image noise is uncorrelated Gaussian, and that the image is locally ergodic and stationary so that local statistics can be used to estimate ensemble features. Unser's method, on the other hand, adaptively computes a linear combination between a noisy image and a restored version of it obtained by an initial filtering. The purpose of this procedure is to improve image restoration performance by using a rather simple structure. In contrast with previous work, this approach is based on a filter of fixed structure rather than on simplified assumptions about a signal model. Simulation and experiment examples indicate that it is capable of reducing noise efficiently while preserving image details. Apparently, image filtering or smoothing using this procedure depends heavily on the structure of the initial filter.

As in most cases, the observed image signal x_{ij} consists of two decorrelated components: true signal u_{ij} and corrupting noise n_{ij} with known variance σ^2 (or a variance estimated from data). This can be expressed as

$$x_{i,j} = u_{i,j} + n_{i,j}. \tag{1}$$

Filtering or smoothing is adopted to improve the signal-to-noise ratio at most points of the image. However, in regions of heavy edges or texture, filtering may degrade the image more than it actually reduces noise. In this case, a compromise would be not to do any filtering on the data. On the other hand, for non-textured or non-edged areas, we may want to filter them using some kind of filter. Accordingly, to obtain an optimal estimate of the true image signal at point (i,j), z_{ij}, a weighted sum of the noisy signal, x_{ij}, and its filtered version, y_{ij}, is constructed as [8]

$$z_{i,j} = a_{i,j}x_{i,j} + b_{i,j}y_{i,j}. \tag{2}$$

with

$$y_{i,j} = \frac{1}{N_R}\sum_{i=-I}^{I}\sum_{j=-J}^{J} x_{i,j}. \tag{3}$$

where y_{ij} is a filtered version of noisy image by a linear operation. I and J are the dimensions of a 2-d image window, and N_R the number of pixels in the window. Note that a_{ij} and b_{ij} are the coefficients that are to be adjusted so that (1) for textured regions, the noisy observation x_{ij} is kept by downweighting the filtered signal y_{ij}; (2) for non-textured regions, the filtered signal y_{ij} is kept by downweighting the noisy observation x_{ij}.

In general, the filter structure discussed above works fine for 2-d images and outperforms some of the other image filtering or smoothing methods. In [8] the initial filter was implemented as a simple moving averaging filter, and the output y_{ij} at point (i,j) from the initial filter was an average of the pixels in a 2-d window centered at that point. However this spatial LS method did not consider the important problem of how to choose the initial restoration filter for specific applications. Research indicated that it suffered from excessive edge smoothing and texture blurring when applied to CT images. For the CT log images discussed here, this 2-d method would smooth out some of the fine details such as checks and splits for instance, Fig.3 (b) shows one such example where several segments of a fine split are lost after image segmentation.

It is noted that the pixel value $x_{i,j,k}$ at one spatial point (i,j,k) on the kth slice is closely correlated with those at its neighboring points on the $(k-1)$th and $(k+1)$th slices in a sequence. Hence one way of improving the initial filter would be incorporating into the filtering process the 3-d interdependence information among pixels in consecutive slices. By incorporating 3-d data into the initial filtering step, filter coefficients a_{ij} and b_{ij} for filtering one image are computed from image data in consecutive slices in a sequence. This initial filter uses consecutive cross-sectional images to perform linear smoothing on the pixels in a volume V with V_R pixels associated with these consecutive images. The output of this initial filter is expressed as

$$y_{i,j} = \frac{1}{V_R}\sum_{i=-I}^{I}\sum_{j=-J}^{J}\sum_{k=-K}^{K} x_{i,j,k}. \tag{4}$$

where I,J,K are the dimensions of a 3-d volume.

To calculate the optimum filter coefficients a_{ij} and b_{ij} for the final estimate of the image signal at each point (i,j) on the kth slice, a least squares (LS) criterion is introduced to minimize the quadratic error

$$\in^2 = \frac{1}{N_R}\sum_{(i,j)\in R}(z_{i,j} - u_{i,j})^2. \tag{5}$$

where R is defined as a M by M window with N_R pixels in it, and z_{ij} is computed using (2) with y_{ij} defined by (4).

Following Unser's procedures [8], the filter coefficients are computed using the following equations:

$$a_{i,j} = 1 - \frac{(1-\rho)\sigma^2}{P(i,j)}. \tag{6}$$

$$b_{i,j} = 1 - a_{i,j}. \tag{7}$$

where $P(i,j)$ is the local estimate of the variance of the estimate residue and is defined as

$$\begin{aligned} P(i,j) &= S_{xx}(i,j) + S_{yy}(i,j) - 2S_{xy}(i,j) \\ &= S_{(x-y)(x-y)}(i,j). \end{aligned} \tag{8}$$

with

$$S_{(x-y)(x-y)}(i,j) = \frac{1}{N_R}\sum_{k=-r}^{r}\sum_{l=-s}^{s}(x_{i+k,j+l} - y_{i+k,j+l})^2. \tag{9}$$

Note that in equation (10), $(1 - r)s^2$ is the residue variance when filtering is not on the signal component, i.e., when the residue variance is due to noise alone. Hence whenever the residue energy is small, the adaptive scheme will allocate a predominant weight to the filtered signal. On the other hand, when the residue energy is greater than this level the weight is shifted to the unfiltered signal. The above argument is consistent with the fact that an unusually large value of P(i,j) is an indication that filtering tends to degrade the signal.

IV. Defects Detection Results

Images filtered using above adaptive filter are then segmented on a image-by-image basis. A histogram is first computed from the filtered image data, and smoothed with a Gaussian function resulting in a smoother curve on which segmentation is based. Fig.1 (c) shows the histogram of one CT log image where different wood materials are marked with different shades for display purpose. An ordinary CT log image consists of pixels representing background, splits, clear wood, knots, and bark. Since bark and knots both have similar CT numbers in the image, they are temporarily treated like a single type of defects. Accordingly, three thresholds are determined on the histogram to segment each image slice into a number of uniform regions, each representing one of these four pixel types. The detected defects will be fed into a recognition component of the vision system where geometrical properties and texture features are to be employed to recognize each individual defect. The recognition component is still being developed.

To determine regions of potential defects, pixels of same greylevel are grouped into connected regions according to the 4-neighborhood connectivity. An integer number (about 10 pixels) is preset as a region size threshold against which all the regions are to be compared. Any region of a size smaller than this threshold value is eliminated by merging it with its nearest neighboring region. This elimination process would usually eliminate false defects resulted from segmentation and retain the well defined regions as defects such as knots, bark, splits and holes. Experiment examples with CT images of a log are given below to show the efficacy of the above described procedures.

CT images used in this study are taken of a 10 feet long red oak log with CT slices being 8 *mm* apart. This sequence of cross-sectional slices of the log consisted of 480 digital images of 12-bit CT numbers representing gray levels from -1024 to 1024 (or 0 to 2047 after a linear transform). For purpose of comparison, several image filtering algorithms were applied to process a number of these 12-bit CT images. The filtered images were then segmented and labeled to produce several defective regions. Fig.2 illustrates one original CT image (a) together with the detection results using the 3σ-filter (b), filtered (c) and segmented (d) images using the modified 3-d adaptive LS filter. It is noted that in Fig.2 (b) there are several false defective regions detected when the 3σ-filter was used. Fig.3 demonstrates the detection results of one CT image (a) using Unser's 2-d method (b), filtered (c) and segmented (d) images using the modified 3-d approach (c). Note that in Fig.3 (d) the fine split is captured almost completely, and the small disconnection is caused by an annual ring passing right through the split.

V. Summary and Discussions

This paper describes an application of CT to the forest product manufacturing industry. It addresses one aspect of the problems of creating a computer vision system that uses CT image data to locate and identify internal defects in hardwood logs. In particular, the paper has discussed the image filtering problem to remove the unwanted high frequence detail from CT log images before image segmentation. A modified version of Unser's adaptive least squares filter is described that (1) is quite suitable for processing CT log images since this approach can be used regardless of the underlying signal model; (2) is computationally very simple. This method has been successfully applied to filter CT images for hardwood log inspection. Research on developing a general methodology for recognizing each individual class of defect in 3-dimension using geometrical properties and texture features is currently underway.

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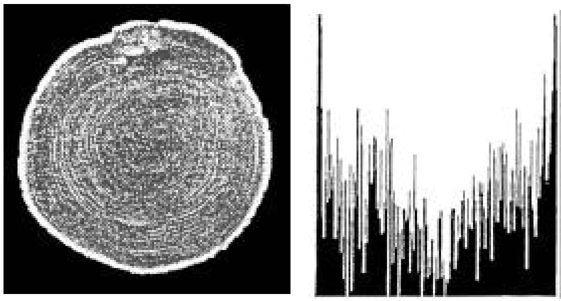
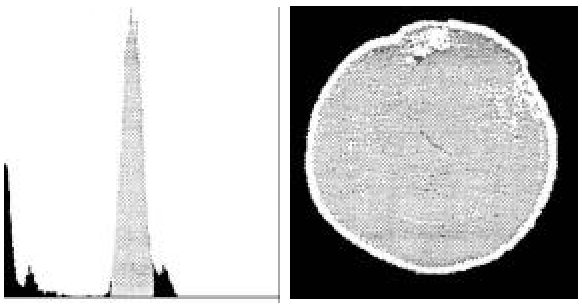
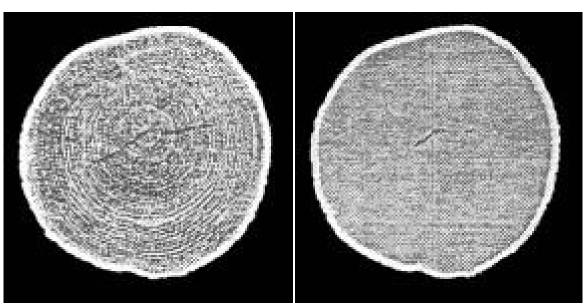


(a) original CT image. (b) graylevel variation.

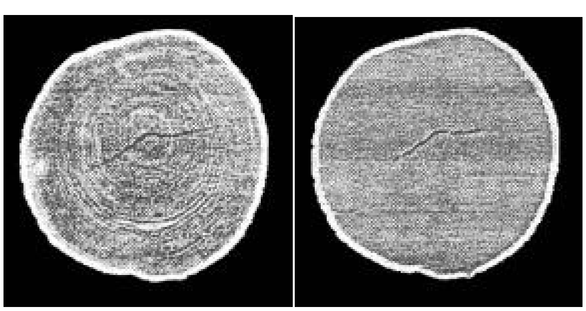


(c) histogram of image (a). (d) segmentation (no filtering).

Fig.1 One example of log image (log1-s64)

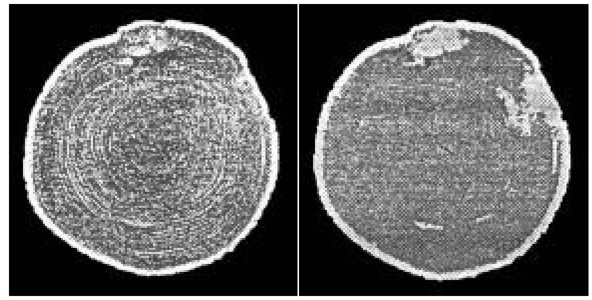


(a) original CT image. (b) using Unser's 2-d method.

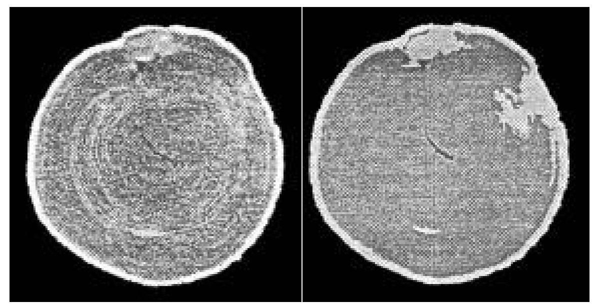


(c) 3-d filtered image. (d) using 3-d method.

Fig.2 Defects detection result 1 (log1-s3)



(a) original CT image. (b) using 2σ method.



(c) 3-d filtered image. (d) using 3-d method.

Fig.3 Defects detection result II (log1-s64)

PROCEEDINGS

THE TWENTY-THIRD SOUTHEASTERN SYMPOSIUM ON SYSTEM THEORY

March 10-12, 1991

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IEEE Computer Society Press

The Institute of Electrical and Electronics Engineers, Inc.