3-D Signal Processing in A Computer Vision System

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Abstract

This paper discusses the problem of 3-dimensional image filtering in a computer vision system that would locate and identify internal structural failure. In particular, a 2-dimensional adaptive filter proposed by Unser has been extended to 3-dimension. In conjunction with segmentation and labeling, the new filter has been used in the computer vision system to successfully detect potential wood defects.

I. Introduction

The research reported in this paper explores a non-destructive testing application of computerized tomography in the forest products automation. 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. 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.

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 internal 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 3-dimensional 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 pre-processing such as filtering or smoothing, direct image segmentation will produce several defective regions with segmentation artifacts that may be caused by the annual ring structures on the image slices. Fig.1 (d) illustrates one segmented image of an original CT slice that has not been filtered. Note the artifacts caused by the annual ring structures.

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 au image estimate from a weighted sum of the observed noisy image and of the output of an initial 2-dimensional linear restoration filter.

Several of these image filtering techniques, including the s -filter, median filter, and 2-dimensional 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 versions of the filtered images 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 has been

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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-dimensional linear adaptive filter. This filter requires no *a priori* knowledge of image properties. In this 3-dimensional algorithm, the first- and second-order adjacencies of pixels are employed to capture the spatial interdependence among these points.

III. Image Filtering by a 3-D Spatial Filter

As in most cases, the observed image signal $x_{i,j,k}$ at spatial location *(i,j,k)* consists of two uncorrelated components: true signal $u_{i,j,k}$ and corrupting noise $n_{i,j,k}$ with known variance (or the noise sample variance which can be estimated on a window of data taken from the background area.). Thus a 3-dimensional image $x_{i,j,k}$ can be expressed as

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

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 (such as splits). On the other hand, for non-textured or non-edged areas(such as clearwood), we may want to filter them using some kind of filtering operation. Accordingly, to obtain an optimal estimate of the true image signal at point *(i, j, k)*, $z_{i,j,k}$, a weighted sum of the noisy signal, $x_{i,j,k}$, and its filtered or restored version, $y_{i,j,k}$, is constructed as (similar to [8])

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

with $y_{i,j,k}$ as a convolution

$$y_{i,j,k} = x_{i,j,k} * h_{i,j,k}. \tag{3}$$

where $h_{i,j,k}$, called the initial falter, is a linear or nonlinear space invariant operator, $y_{i,j,k}$ is an initially restored version of noisy image by the operator. Note that $a_{i,j,k}$ and $b_{i,j,k}$ are the coefficients that are to be adjusted so that: (l) for edged regions(such as splits), the noisy observation $x_{i,j,k}$ is kept by down weighting (through reducing $b_{i,j,k}$) the restored signal $y_{i,j,k}$; and (2) for non-edged regions(such as clear wood), the initially restored signal $y_{i,j,k}$ is kept by down weighting (through reducing $a_{i,j,k}$) the noisy observation $x_{i,j,k}$.

In general, the 2-dimensional filter structure discussed in [8] works fine for 2-dimensional images and outperforms some of the other image filtering or smoothing methods. In [8] the 2-dimensional initial filter $h_{i,j}$ was implemented as a simple 2-dimensional moving averaging filter, and the 2-dimensional output $y_{i,j}$ at point *(i,j)* from this initial filter was an average of the pixels in a 2-dimensional 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 bluring when applied to CT images. For the CT log images discussed here, this 2-dimensional method would smooth out some of the fine details such as checks and splits. For instance, Fig.2 (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 a point *(i, j, k)* on the *kth* slice is closely correlated with those at its neighboring points on the *(k* - l)th and *(k*+ l)th slices in a sequence. Hence one way of improving the filter would be finding the optimal solution for a least squares problem defined in a 3-dimensional volume. By solving this 3-dimensional problem, filter coefficients $a_{i,j,k}$ and $b_{i,j,k}$ in equation (2) can be computed from image data in consecutive slices in a sequence. This extended 3-dimensional filter also uses consecutive cross-sectional images to perform the initial image restoration on the pixels in a volume V_y from these consecutive images. The output of this initial filter is expressed as

$$y_{i,j,k} = \sum_{l=-L}^{L} \sum_{m=-M}^{M} \sum_{n=-N}^{N} x_{i-l,j-m,k-n} h_{l,m,n}. \tag{4}$$

where *L, M, N* are the proper dimensions of the 3-dimensional volume on V_y which the initial image resonation is performed, and their typical values are from 1 to 3, depending on input images. Operator $h_{i,j,k}$ can be chosen as the averaging filter, the 3-dimensional Gaussian smoothing filter, or other linear or nonlinear forms.

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

$$\epsilon^2 = \frac{1}{N_r} \sum_{(i,j,k)\in V} (z_{i,j,k} - u_{i,j,k})^2. \tag{5}$$

where V is defined as a 3-dimensional cubic with dimension D_v and N_r is the number of pixels in the cubic. Typical value for D_v is from 3 to 7. In order to find the optimal solution for the filter coefficients $a_{i,j,k}$ and $b_{i,j,k}$, let us assume for the time being that these two coefficients are constant over the volume *V* though they are later allowed to change at different spatial point. Note that $z_{i,j,k}$ is computed using equation (2), and that $y_{i,j,k}$ is defined by equation (4).

Following the procedures similar to Unser [8], the filter coefficients are computed by finding the optimal solution to equation (5). This can be accomplished by first setting to zero the partial derivative of in equation (5) with respect to $a_{i,j,k}$ and $b_{i,j,k}$, and then replacing unknown variables in a system of equations by their expected values. Matrix manipulation similar to that in [8] leads to the following solution:

(6)

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

where constant called the residual noise correlation coefficient, is computed as

$$\rho = h(0,0,0) = \frac{1}{(2L+1)(2M+1)(2N+1)}. \tag{8}$$

if $h_{i,j,k}$ is defined as an averaging filter. *P(i,j)* is the local estimate of the variance of the estimate residue (i.e., the estimation error), and it is defined by

$$\begin{aligned} P(i,j,k) &= S_{xx}(i,j,k) + S_{yy}(i,j,k) - 2S_{xy}(i,j,k) \\ &= S_{(x-y)(x-y)}(i,j,k). \end{aligned} \tag{9}$$

with the general expression for $S_{uv}(i, j, k)$ as

$$S_{uv}(i,j,k) = \frac{1}{V_r} \sum_{(i,j,k)\in V} u_{i,j,k} v_{i,j,k}. \tag{10}$$

Note that in equation (6), (1 - 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. Wood Detection Results

Images filtered using above adaptive filter are then segmented on an image-by-image basis. A histogram is first computed from the filtered image data, and smoothed with a Gaussian function resulting in a smoother histogram on which segmentation is baaed. 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 the same greylevel are grouped into connected regions according to the 8-neighborhood connectivity. 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 severed defective regions. Fig. 2 illustrates an original image (a), the segmented images using the o-filter (b) and the 3-dimensional filter (c). Fig. 3 shows a smoothed image using 3-d filter (a), the segmented images after smoothing by 2-d (b) and 3-d (c) adaptive filters. Finally, Fig. 4 shows three segmented images after smoothing using 3-d Gaussian operator (a), 2-d (b) and 3-d (c) moving average operators as the initial restoration filters, respectively.

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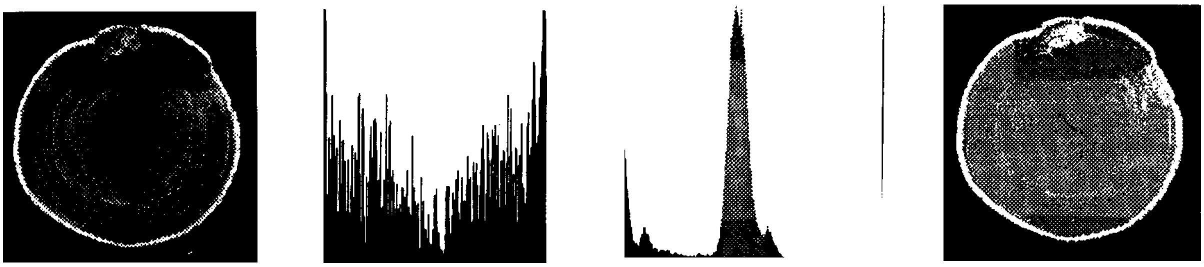
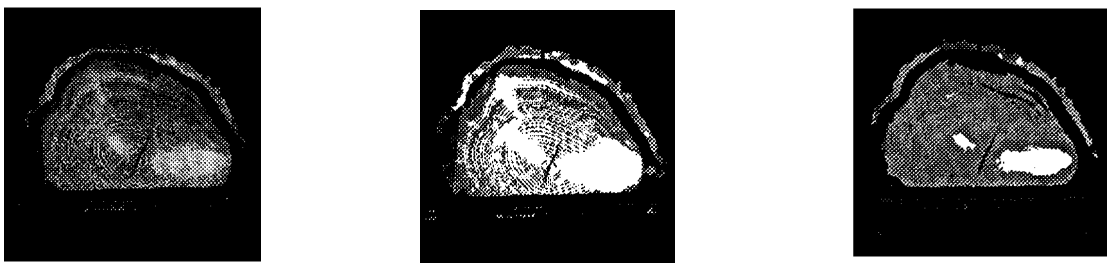


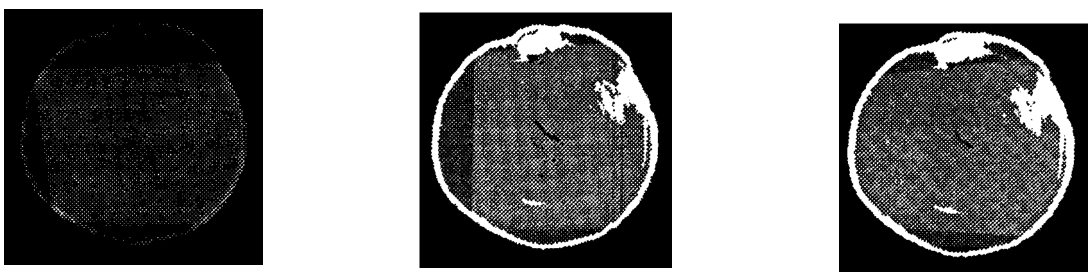
(b) graylevel variation. (c) its histogram. (d) segmentation (no filtering).

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



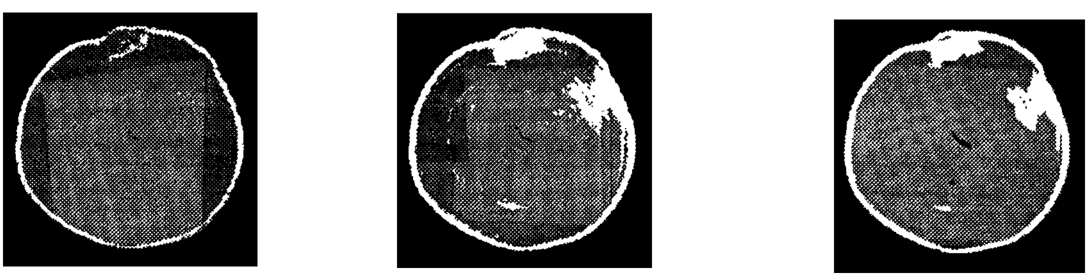
(a) original CT image. (b) segmentation after filtering. (c) segmentation after 3-d adaptive filtering.

Fig.2 Defect detection result I (rkll-s22).



(a) restored image by 3-d method. (b) segmentation after 2-d filtering. (c) segmentation after 3-d filtering.

Fig.3 Defect detection result II (logl-s64).



(a) 3-d Gaussian. (b) 2-d moving average. (c) 3-d moving average.

Fig.4 Results by 3 initial filters $h_{i,j,k}$ (logl-s65).

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