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AN AUTOMATIC TREE RING MEASUREMENT SYSTEM

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Abstract

This paper describes a robust and ***portable*** *tree ring parameter measurement system, which has a potential of surpassing state-of-the-art systems. A radially movable hand-held scanner is utilized. The problem of different vertical resolution in the image is handled using vertically adaptive filters in the subimages. A two-step segmentation strategy is taken. The periodicity of tree rings is first estimated in each subimage using the "Gray Level Gap Length" method. Then the result serves as input parameter in the succeeding processes.*

Scanning and processing the same tree sector 25 times, error analysis shows that the system gives reproducible results. Comparison to manual measurements shows that the system is quite reliable. The robustness of the system has also been demonstrated by measuring different types of trees.

Introduction

Tree rings of evergreens are an important feature which characterizes the biological and physical properties of trees. They also reflect the environmental conditions in the growing season. A tree ring is normally composed of an earlywood and a latewood portion. Earlywood fibres have a larger volume, thinner fibre-wall, and lighter colour compared to latewood fibres. Their bonding and strength properties are also different.

Tree ring measurement has gain an increasing interest in forest research, wood technology, dendrochronology, dendroclimatology, and pulp and paper industry. Existing measurement systems for automatic tree ring registration are mainly based on optical cameras [1] [2] [3]. Insufficient resolution of the cameras are the main problem which reduce the efficiency of such systems. So, the measurements are often rough estimations in some specific areas, or are registered only according to 1 or 2 radii along the scanning direction. The width of the earlywood/latewood portion is usually not measured.

We present a new tree ring measurement system which is portable, robust and, nevertheless, precise. Our system utilizes a PC and a radially movable hand-hold scanner. The centre of the scanning circle is placed at the pith while scanning on a cross section of a log. It measures a whole tree sector instead of scanning along a tree diameter as one usually does. The resolution is also quite high, 400 dpi.

A polar-to-cartesian coordinate transform is performed automatically by the scanner, such that circular tree rings appear as vertical stripes in the image. This texture feature is first extracted as a kind of self-learning process. The knowledge is utilized to control other parameters in the succeeding processes. A simple scheme in Figure 1 describes the strategies of the system.

In the output, each tree ring is characterized in terms of its position, and the width of its earlywood and latewood portions. A number of parameters are

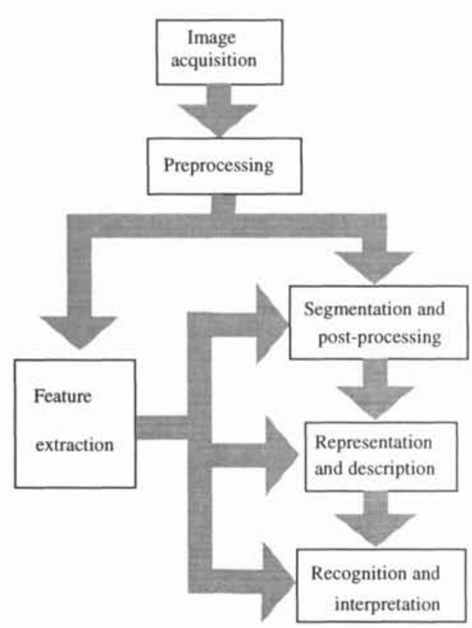

Figure 1
The scheme of the tree ring image analysis algorithm.

extracted from the estimated tree ring distribution to characterize the quality of the logs. These parameters are used in the system evaluation.

Two-step Segmentation Algorithm

Reliable measurements of the image objects depend on the result of the image processing, especially on the precision of the image segmentation.

In the present images, the contrast between the earlywood and latewood portions is quite low, with sawing scratches and other types of noise. The width and distribution of tree rings varies greatly from tree to tree, and within each tree. Typically, the ring width can vary from 0.3mm to 10mm. Global thresholding methods can not segment the latewood portions from the earlywood. Local thresholding strategies normally employ a fixed window size. If the window is too big, the narrow rings will not be detected. But if the window is too small, the broad rings will be thinned and more noise is introduced. To obtain a proper segmentation result, the size of the window should vary according to the width of the tree rings.

Since the width difference between adjacent tree rings are normally small, we divided the image horizontally into several overlapped subimages. Then a two-step segmentation strategy is applied: first extracting local information about periodical features of the tree rings, and then using this information to control the adaptive thresholding.

The periodicity of the tree rings in each subimage is estimated by the weighted Gray Level Gap Length Matrix (GLGLM) [4]. The GLGLM is based on measuring the gap lengths of each gray level. It characterizes the image by statistical description of the peaks and valleys. The bright earlywood and the dark latewood of tree rings can therefore be measured according to the gaps of each other. The estimated ring width is the sum of the maximum possible gap lengths of those two portions.

We define $r(n)$ as the periodicity of tree rings in the subimage n, where $n = 1, 2, ..., N$ and N is the total number of the subimages. Then

$$r(n) = L_{black}(n) + L_{white}(n) \tag{1}$$

where $L_{black}(n)$ and $L_{white}(n)$ are the gap length values in the subimage n which reach the maximum value of $S_{black}(l)$ and $S_{white}(l)$ respectively. Here

$$S_{black}(l) = \sum_{g=0}^{\mu_0 - 1} A_w(g, l) \tag{2}$$

$$S_{white}(l) = \sum_{g=\mu_0}^{G-1} A_w(g, l) \tag{3}$$

$$\mu_0 = \frac{\sum_{g=0}^{G-1} h(g) \cdot g}{\sum_{g=0}^{G-1} h(g)} \tag{4}$$

where $h(g)$ is the histogram value of gray level g, G is the number of gray levels, and $A_w(g, l)$ is the weighted GLGLM as defined by Wang et al. [4].

The window of the thresholding process is chosen as $3 \times \alpha \cdot r(n)$, where α is a constant. Such a horizontally oriented rectangular shape is used to select the vertically directed tree ring features meanwhile to eliminate the horizontally directed noisy signals.

A local thresholding method suggested by White and Rohrer [5] is modified such that the threshold depends both on the local statistical moments and on the estimated ring width in the subimage, i.e.

$$t = v(i,j) - k(r(n)) \cdot \sigma(i,j) \tag{5}$$

Here, t is the adaptive threshold, $k(r(n))$ is a function of the periodicity for the subimage n, $v(i, j)$ and $\sigma(i, j)$ are the mean value and the standard deviation in a neighbourhood of the pixel (i, j) respectively. The definition of the function $k(r(n))$ is trying to add more bias towards black in the subimages having broad rings, where the earlywood portions are normally much wider than the latewood portions. In this case, the local mean will tend towards white. Increasing the weighting function is necessary to avoid a widening of the object and introducing more noise.

Noise Removing and Image Interpretation

The special manner of image acquisition has implied a coordinate transform which creates an uneven vertical resolution. During the movement of the scanner, the pith of the tree section is scanned repeatedly. So, the maximum magnification in the vertical direction is obtained near the pith. This results in different noise characteristics from left to right in the image.

Taking R as the width and r as the distance to the left margin of the image where the pith located, from plane geometry we know that the magnification ratio at column r is proportional to r / R. In order to process noise evenly, a variable vertical resolution is imitated by a column shaped filter of size $l(r) \times 1$, where $l(r)$ is a function of the distance r from the left margin to the column considered. To simplify the implementation, $l(r)$ is replaced by $l(r_n)$, for $r \in$ subimage n. Here r_n is the centre column of the subimage. So, $l(r_n)$ is a constant within each subimage but varies among subimages. It is large when the resolution is low, and vice versa.

This variable filter shape is efficiently utilized by the pre- and post-processing to remove the noise as well as to link the broken objects, since the objects are typically vertical stripes. A slight smoothing is applied in the pre-processing to preserve the narrow tree rings. Most tasks of the noise removing are performed in the post-processing by median and morphological operations.

A region encoding method is chosen to represent the latewood portions as the objects. The *maximum height* of the region descriptor is taken as a criterion to further remove large noisy regions. A threshold h for this parameter is defined as

$$h = r(n)/2 + C \cdot l(r_n) \quad \textbf{(6)}$$

where $r(n)$ and $l(r_n)$ are as defined above, and C is an input constant. This is an effective and fast way to remove large noisy blocks, which is often a difficult job for a smoothing filter.

Then, the remaining ring pieces are linked according to their *orientation angles* and other contextual restrictions. Here again, the periodicity of the rings, $r(n)$, and the variable vertical resolution, $l(r_n)$, are also among the link criteria. Finally, the width and position of each latewood portion, and thereby of each ring, are determined by an average strategy along the regions.

Results and Discussion

The logs need to have a relatively even and clean cross section for image acquisition. If they are directly taken from a saw mill, a slightly sanding is usually applied to remove the dirt and rough wood fibres. Figure 2a is an image of a tree section. The noisy scratches can be clearly seen, while the narrow rings in the right part of the image are rather blurred. Figure 2b is the resulting image after all the image processing strategies. It shows that both broad and narrow rings in the same image are properly segmented, meanwhile the noise has been eliminated efficiently. Figure 2c is the estimated distribution of the earlywood and latewood portions which is repeated in the y-direction to make the result more intuitive. Comparing these three figures, we can conclude that the estimations are quite reasonable.

Several parameters are extracted from the estimated tree ring distribution. Examples are shown in **Table 1**. Here the weighted parameters are obtained by the sums of each ring (or portion) width weighted by its radius, since the width of the rings near the bark is more significant than those near the pith. These parameters give some characterizations of the quality of the logs.

The stability of the system is tested by scanning and processing one tree sector 25 times. The statistics in **Table 1** show that the variation in processing results is quite small. The *coefficient of variation* σ/μ is less than 5% for all extracted features.

The reliability of the system is evaluated by comparison with human visual measurements performed on the same tree sector using a light microscope. 25 different radius are measured. From **Table 1** we see that the values of *coefficient of variation* are larger for visual measurement except for *Number of Rings*. This is not a surprise. Since most of the tree rings are not really circular, measurements along different radii will give different results. It also proves that measuring a whole sector is more reliable than measuring only a few radii. On the other hand, the *Number of Rings* can be counted quite precisely by visual measurement, whereas our system often suffer more problems from noise and very thin rings.

It is found that the *mean difference* between these two data sets is less than 0.3 mm for the *Radius* of the tree, and less than 0.06 mm for all other width features. The estimated widths of earlywood and latewood are quite precise.

Table 1 Comparison of two measurements

Name of Parameters	Coefficient of Variation σ/μ		Mean Difference $\overline{\text{X-Y}}$
	by image processing X	by visual measurement Y	
Number of Rings	0.029	0.026	0.06000
Radius (mm)	0.005	0.028	-0.22010
Average Width of Rings (mm)	0.027	0.029	-0.00666
Weighted Width of Rings (mm)	0.032	0.036	0.05377
Average Width of Latewood Portion (mm)	0.021	0.079	-0.01155
Average Width of Earlywood Portion (mm)	0.033	0.043	0.01378
Weighted Width of Latewood Portion (mm)	0.030	0.084	0.01236
Weighted Width of Earlywood Portion (mm)	0.041	0.044	0.04106
Relative Area of Latewood	0.028	0.068	-0.00006
Relative Area of Earlywood	0.013	0.030	0.00006

The robustness of the system is tested by choosing three groups of tree discs with ring width varying from 0.3mm to 10mm. 12 different tree discs are selected and processed using the ***same*** set of the initial parameters. From **Table 2** we see that only an average error of about 1 ring is found for the

Number of Rings feature. The result shows that the system works also well for both broad and narrow rings on different trees.

The robustness is important for an industrial application system. Because of the unpredictable variation in input images, it is often difficult to use a fixed set of parameters. However, the problems have been reduced to a minimum by the position-dependent and local property-dependent strategies used in this system.

Table 2 Estimated Ring-number of Different Tree

Class of Rings	Tree Number	Observed No. of Rings	Calculated No. of Rings	Calculation Error
Broad 4-10 mm	1	16	17	1
	2	16	17	1
Medium 1.5-5 mm	3	50	49	-1
	4	16	16	0
	5	16	17	1
	6	13	12	-1
	7	20	20	0
	8	18	17	-1
Thin 0.3-1.5 mm	9	33	34	1
	10	26	25	-1
	11	27	26	-1
	12	39	38	-1

Conclusion

The error analyses show that the system is not very sensitive to small damages and noise. It can endure large differences in ring widths and distributions. And it is suitable for both small and relatively large trees. More important, the time-saving and labor-saving is huge.

A clear principle has run throughout the whole system design, i.e., using as much information as possible from the image itself to guide the processing, such that the parameters of the algorithms are automatically adapted to different input images and to local variations within each image. This tree ring measurement system can therefore endure a relative large variation in input features and the whole analysis can be performed automatically in a few seconds after the image acquisition.

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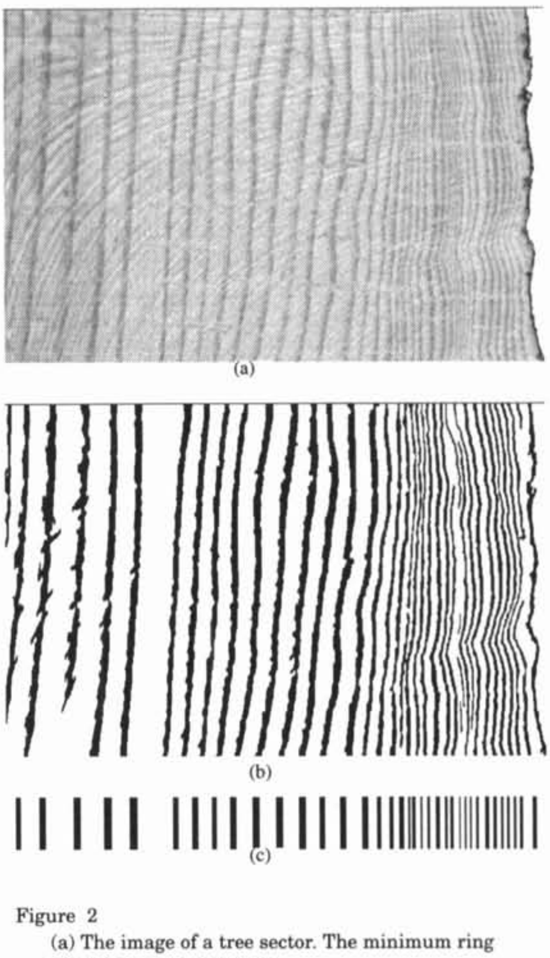

Figure 2
(a) The image of a tree sector. The minimum ring width is less than 0.3mm.
(b) The output image after all the image processing treatments.
(c) The estimated distribution of tree rings by the system (repeated in the y-direction to make the result more intuitive).