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***Abstract*—Tree ring analysis can provide useful data like life length and yearly growth of a tree for dendrochronologists. The analysis can help them to researches on past ecologies, climate, environmental changes and archaeology. Because counting number of rings and measuring widths are time-consuming and hard tasks, an automatic system is recently demanded. This paper proposes a method to analyze tree rings in order to automate the above tasks. The method consists of a segmentation processing to detect the tree rings image from a gray image, a processing to reduce the noise from the binary image, and a measuring processing to count the number of rings. One of known difficulties is the existence of obstacles such as scars and noises against the segmentation. We effectively use statistical approach to cope with this difficulty. The experiments show that the margin of error in the measurement of the number of the rings is about ±10% and the proposed method has an advantage in the accuracy when comparing with traditional methods.**

Keywords: image processing, tree rings, automatic measurement, binary image, dendrochronology, statistical approach

I. INTRODUCTION

A. Background and research purpose

Image recognition is an all-embracing research field that has many applications in natural sciences. One of them is dendrochronology. Dendrochronology is a subject about dating based on the analysis of properties of tree rings and other elements on a cross section of trees. A form of tree rings is an evidence of growth of trees because most trees make one ring at the bark for each year. The number of rings of a tree can infer the age of the tree. The width between rings can reflect the climate of the growth term. With enough nutrients and a long growth term it will grow a wide ring while with poor conditions or a short growth season it will grow a narrow ring. With several samples of the tree rings, dendrochronologists can build a ring chronicle which is used for past ecologies, climate research, environmental changes and archaeology.

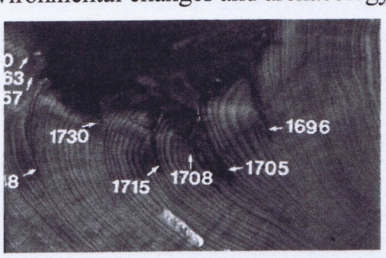


Figure 1. Dating on the cross section for dendrochronology

Dating on the rings, as shown in Figure 1, was originally based on a manual work. The manual detection of rings and counting its number is a time-consuming task. With image recognition machines it can be solved automatically. The automatic machine saves much time and labor for scientists. Several functions may be most useful for researchers: counting the number of rings, measuring the width between close rings, and marking rings with different colors. What advanced is that this research aims to develop a recognition system to measure the rings automatically without setting parameters of different images manually. The accuracy of the measurement is the most important property of the system. To increase the accuracy, statistical approach is proposed in this paper.

B. State of the art

Many methods for tree rings analysis exist [1] [2] [3] [4] [5]. An important core in these methods is to detect the rings. If rings can be shown clearly, the counting work will be relatively easy. All the methods are based on gray images, so the first step is changing color image into a gray one.

Pierre Soille [1] uses a series of morphological functions to detect rings. The input gray image after a series of operations will be made as a marker. With the same image after the gradient operation the marker takes a watersheds operation. Then rings can be detected. The parameters in the morphological functions are based on the known width of rings and the width between close rings. Steven Corner's method [2] is based on the canny filter. Some characteristics of rings (known width between close rings) are used to replenish the lack of rings and reduce the noise between rings. Therefore, the parameter of the canny filter must be set manually. Didier Demigny [3] and M. Sarifuddin [4] use predetermined waveforms around edges of rings. They develop filters to smooth the noise to get edges of rings. Hayet Laggoune [5] uses M. Sarifuddin's filters to get the edges and use Steven Corner's method to correct the result and label the rings. In summary, existing techniques are based on manual or semi-automatic setting of parameters. In other words, few of them are interested in counting rings but interested in getting outlines of tree rings manually.

C. Research Issues

In this paper, the most important difference between the proposed method and existing ones is to develop an automatic system without setting parameters manually. What is advanced is a statistical approach to increase the accuracy.

Supervisor: Prof. Hiroshi SAKO

The important step of the system is detection of rings. If rings can be shown clearly, counting rings can be done with high accuracy. The major difficult issues in this research are: 1) scars crossing the rings, 2) noises on the cross section (shown in Figure 2), and 3) self-tuned method for the automatic system.

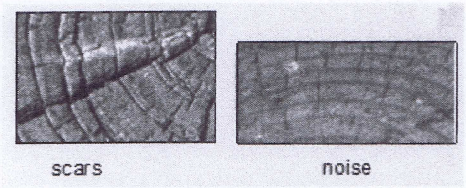


Figure 2. Difficulties in this research

II. METHOD

A. *System outline and approach to solve the difficulties*

Figure 3 shows the outline of the system which consists of three parts; the segmentation of the tree rings from a gray input image, the noise reduction from the segmented image, and the measurement of the number of rings. The segmentation includes the binarization after smoothing the gray image by a Gaussian filter. The reduction of noises is based on the size of the noise in order to cope with the issue 2. The measurement of the number of rings is composed of the detection of the center and the statistical analysis using many line-profiles passed through the center in order to cope with the issue 1. All parameters in the methods are self-adaptive in order to realize the issue 3.

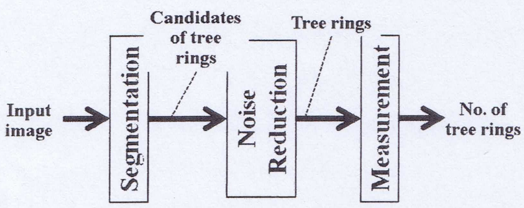


Figure 3. Outline of the system

B. *Segmentation of the rings*

After smoothing the gray image by a Gaussian filter, the binarization of the gray image is executed. To cope with the shading of the image, we examine two methods; one is based on Otsu's method (OM) [6], which gives an adaptive threshold in each of local area with a fixed size. The threshold is calculated by statistical analysis in two-class-problem. The other is the Adaptive Threshold method (AT). The threshold $T(x,y)$ is determined as a multiply and summation operation using Gaussian weights and pixels in a block (block size: Bs) centered at (x, y). The binarization by AT is based on this threshold.

C. *Reduction of noises*

Based on the assumption that small connected components in the binary image must be not a part of the ring, the components are removed as noises. In order to measure the size of the components, the labeling [7] is executed and the same-labeled components of which number of pixels is less than a threshold, s, are removed from the original segmented image.

D. *Measurement of the number of rings*

1) The center detection: The whole image will be scanned toward the horizontal direction at each y coordinate and the vertical direction at each x coordinate, separately. The number of black-pixel-parts continued by 2 to 20 are counted (as ring candidate parts) in a scan. The other cases such as too short or too long parts are considered as a scar or a noise. The y coordinate having the maximum number and the x coordinate having the maximum number are regarded as the center coordinates. Figure 4 shows an example of a scan result at a y coordinate, where the horizontal axis corresponds to the coordinate x of the image, and the vertical axis shows the pixel value (255 means white and 0 means black). Figure 5 shows a measurement example, where the horizontal axis corresponds to the coordinate x of the image, and the vertical axis shows the measurement result (the number of black parts).

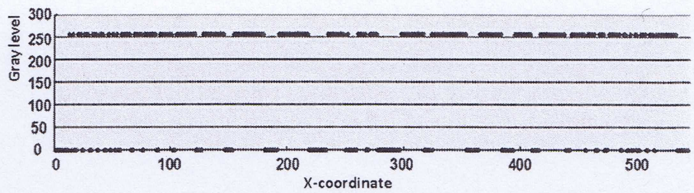


Figure 4. Binary pixels on a line profile

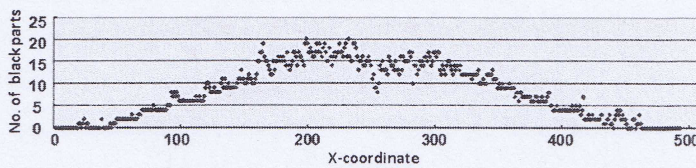


Figure 5. Number of black parts

2) Statistical analysis of line-profiles: For further reduction of the influence of the scars and misclassified elements, a statistical approach has been developed here. About 100 different angled line-profiles across the center are taken, and the line-profiles with the neighboring angles are summed and averaged at each angle. After this noise reduction of the profiles, the number of connected parts is measured in the same way as mentioned before. Figure 6 shows an example of the number detected at each angle (horizontal axes in the figure). Then, the number with a highest frequency is regarded as the number of the rings.

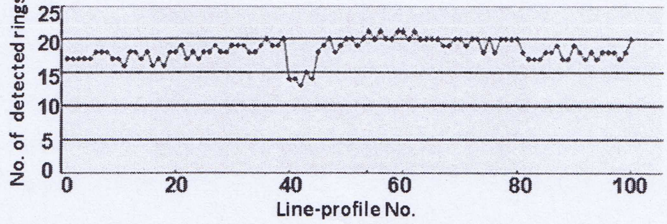


Figure 6. Number of ring candidates at each angle.

III. Experiment

A. Experiment environment

The experiment has done in a PC with I7 CPU and 8GB RAM. The OS is window 7. The software is based on VC++ 2008 and OpenCV library. The test images in Figure 7 are all taken from websites [8] with different range of intelligibility. The outside part of the tree's cross section is deleted manually.

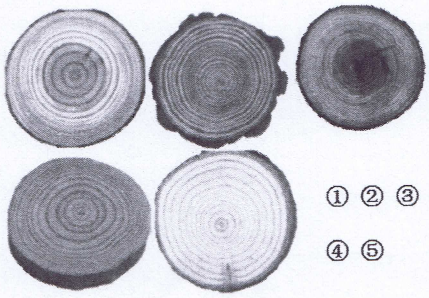
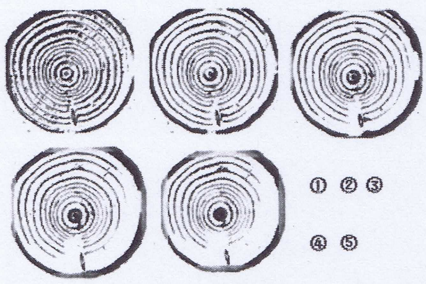


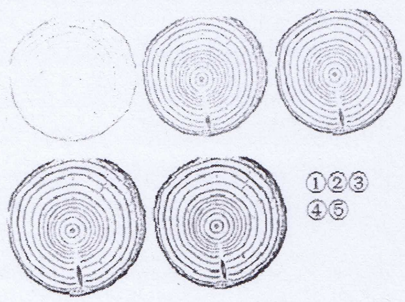
Figure 7. Original images for experiment

B. Evaluation of the segmentation of the rings

Figure 8 shows the segmentation results of the original image No. 5. Figure 8 (a) shows the results obtained by the OM with moving windows. The window pixel-sizes, *Ws* in the figure are 5, 10, 20, 30, and 40. Figure 8 (b) shows the results obtained by the AT. The block sizes, *Bs* in the figure are 3, 7, 11, 15, and 21.



(a) Results by the OM with different window sizes



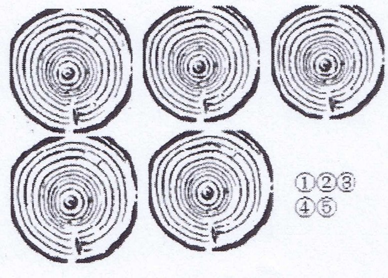
(b) Results of the AT with different block sizes

Figure 8. Segmentation results with different block sizes

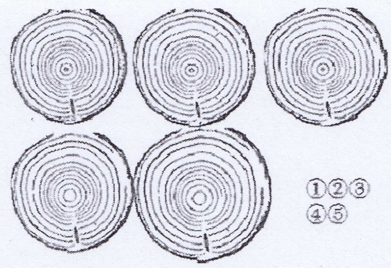
In the OM, small windows produce more noise while large windows miss more parts of rings. Taking into consideration of a ratio of the false positive and negative, we conclude that the window size, *Ws*=10, gives the best segmentation. In the AT, the block size, *Bs*=21, gives the best segmentation as shown in the figure. As for the processing time, The AT is about ten times faster than that of the OM.

C. Evaluation of the reduction of noises

Figure 9 (a) shows the reduction results by several absolute size-thresholds applied the image by the OM with the window size, 10. In the figure, the images are the results with the size threshold, *s*=10, 50, 100, 150, 200, respectively. Figure 9 (b) shows the results in the AT using the block size 21.



(a) Application to the images by the OM



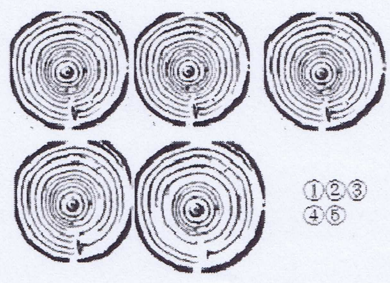
(b) Application to the images by the AT

Figure 9. Noise reduction by absolute size thresholds

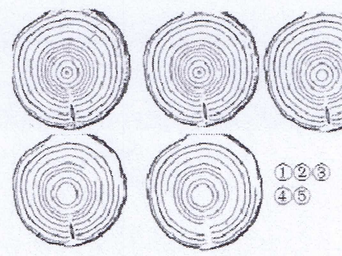
Taking into consideration of a ratio of the false positive and negative, we conclude that the absolute size threshold, 150 in the OM, 100 in the AT give the best segmentation, respectively.

The absolute size threshold is simple enough to implement, but its disadvantage is no tolerance against the change in dimensions of the image. Therefore, we examine a relative size threshold which is based on the assumption that *t*% pixels out of the total number of black pixels are noise.

Figure 10 (a) shows the results of different $t = 0.1$, 0.5, 1, 5, and 10 in the OM, and Figure 10 (b) shows the results of different $t = 1$, 5, 10, 15, and 20 in the AT.



(a) Application to the images by the OM



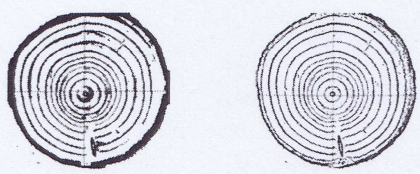
(b) Application to the images by the AT

Figure 10. Noise reduction by relative size thresholds

Taking into consideration of a ratio of the false positive and negative, we conclude that the relative size threshold, t=1, in Otsu's method, t=5, in adaptive threshold method gives the best segmentation, respectively.

D. Evaluation of the center detection

Figure 11 shows the center detection results of the images detected in different segmentation; Figure 11 (a) shows the segmentation by the OM with Ws=10 and t=1, and Figure 11 (b) by the AT with Bs=21 and t=5. They all get satisfied result.



(a) Result of the image by the OM (b) Result of the image by the AT

Figure 11. Examples of detected centers

E. Effect of statistical analysis of line-profiles

Table 1 shows the ring numbers measured when the number of line-profiles changes. The segmentation method is the AT with Bs=21 and t=5. The line-profiles are randomly selected from 10 to 100 and we measure the number of rings by the method mentioned in the previous chapter.

Table 1. Number of the rings as the number of line-profiles changed

Number of line-profiles	Test image No.				
	1	*2*	*3*	*4*	*5*
10	18	14	16	9	11
20	16	15	15	8	10
30	16	15	17	9	10
40	15	16	17	10	11
50	15	16	17	10	11
60	16	16	17	10	11
70	16	16	17	10	11
80	16	16	17	10	11
90	16	16	17	10	11
100	16	16	17	10	11
Manual measurement	17	16	21	12	11

As the number of line-profiles increases, the detected number of the rings is stable and come to the correct number. This confirms that the statistic approach has an advantage.

F. Comparison between the accuracies

Table 2 shows the ring numbers measured by the proposed method. The examined images correspond to ones obtained by segmentation methods with various conditions. Cases using a typical segmentation method called canny filter (CF) also additionally evaluated. Its parameters are a low threshold (Lt) and a high threshold equivalent to 3 times of Lt.

Table 2. Measurement of the rings by several segmentation methods

Segmentmethod	Conditions	Test image No.				
		1	*2*	*3*	*4*	*5*
OM	Ws=10, s=150	14	15	16	10	10
OM	Ws=10, t=1	15	15	17	**11**	10
AT	Bs=21, s=100	**16**	18	**19**	**11**	10
AT	Bs=21, t=5	**16**	**16**	17	10	**11**
CF	Lt=20	15	18	15	10	9
CF	Lt=50	14	11	15	6	4
Manual measurement		17	16	21	12	11

In summary, the proposed measurement method of the number of rings works well to all the samples with the segmentation by the AT, and the margin of error is all about ±10%. The method also works well to samples 4 with the OM. The worst cases are the measurements by the CF in this experiment because of the mis-detection of the center.

IV. Conclusion

The measurement method of the number of tree rings by statistical analysis was proposed. The analysis is based on the truth that many trials to measure the rings towards different angles from the center converges a correct answer. The accuracy still somewhat depends on the segmentation quality, but on average, the method works well. The margin of error in the measurement of the number of the rings is about ±10%.

The future work includes a development of the method to cope with more complicated images, of an automatic method for the elimination of the background beside the cross section of the trees and increase the efficient of the whole system.

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