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Multi-Objective Optimization on Pore Segmentation

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Abstract

In order to segment pores automatically without parameters set manually, it is necessary to design an adaptive algorithm which may be applied for different kinds of hardwood cross-section images. A novel adaptive method is proposed in this paper to evaluate the optimal threshold of closed region area for pore segmentation. Based on area histogram, this method classifies the regions into two classes with maximum between-class variance. Experiment shows that the method has more effective to diffuse porous wood and pore solitary, but many pores cannot be segmented for semi-diffuse porous wood, ring-porous wood or other pore combination except solitary pore. According to the domain knowledge of wood science, second objective function is used to improve the pore segmentation performance. Further experiment on genetic algorithm demonstrates that the task of pore segmentation can be completed successfully for all kinds of hardwood by multi-objective function.

1. Introduction

Pores in cross-sections are often studied as an important feature for hardwood identification. So researchers applied image processing technology into pore extraction for efficient, accurate intelligent wood identification. To obtain pores from images, usual method is image segmentation. Most image segmentation methods can be classified into three groups: the analytical, the empirical goodness and the empirical discrepancy groups. Each group has its own characteristics [1]. Qi uses mathematical morphology methods, with the advantage of noise-robust and high-speed in image segmentation [2], to segment the pores from the background and gets a good result [3]. But he's method has a common drawback that the sound segmentation result relies on the parameter of area that can select pore from fiber and longitudinal parenchyma. This is a threshold related to image or wood species that always set manually by experience. In order to segment pores automatically without parameters set manually, it is necessary to design an adaptive algorithm which may be applied for all kinds of hardwood cross-section images.

In this paper, a novel adaptive method based on area histogram of the similar circle regions is proposed to evaluate the optimal threshold for pore segmentation. The idea comes from Otsu's algorithm, which is a popular thresholding technique for image segmentation with gray scale histogram [4]. Our method is based on area histogram of the similar circle regions, which sorts all closed region according to area after image segmentation and counts the number of same area pores; then use maximum between-class variance to divide closed region into two classes. The large one is pore. Experiment shows that the method has more effective to diffuse porous wood and solitary pore, but many pores cannot be segmented for semi-diffuse porous wood, ring-porous wood or other pore combination except solitary pore. On account of pore sizes are more similar for each other in images of diffuse porous wood and solitary pore, but vary greatly in other images. Finer results cannot be acquired only by using maximum between-class variance method.

The application of evolutionary algorithms in multi-objective optimization is currently receiving growing interest from researchers with various backgrounds. In contrast to single-objective optimization, both fitness assignment and selection must allow for several objectives with multi-criteria optimization problems. To overcome the shortage of the maximum between-class variance method mentioned above, we use aggregation-based strategy [5], aggregate the objectives into a single parameterized objective. According to the domain knowledge of wood science, which is little proportion of pores in cross-sections, second objective function about average area of closed regions is used. Further experiment on genetic algorithm demonstrates that pore segmentation can be completed successfully for all kinds of hardwood by multi-objective optimization.

The rest of this paper is organized as follows. In section 2 we present the segmentation method for all closed region by mathematical morphology. Following

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that, in Section 3, is a description of how to calculate pore size threshold based on maximum between-class variance. Section 4 discusses the implementation of thresholding based on multi-objective genetic algorithm. After that, we give out the experiment results in section 5. Finally, the paper comes to a conclusion in section 6.

2. Mathematical morphology based image segmentation

In the early 1960s, Matheron invented mathematical morphology as the part of binary image processing [6]. Mathematical morphology is becoming increasingly important in image processing and computer vision applications for object representation, recognition, and defect inspection since. Because it provides powerful tools to extract the main features of a digitized image [7], we can use it to build the filters that ease region segmentation of wood anatomical structure.

We can apply the two basic mathematical morphology operations of *erosion* and *dilation* to image edge detection. We think that all images are gray scale in this paper.

Assuming $f(x, y)$ is the input image function of gray scale, $b(x, y)$ is the given structural element, and is defined on R^2. The *dilation* operation is defined as follows:

$$(f \oplus b)(x,y) = \max\{f(x-x', y-y') + b(x',y') \mid (x',y') \in D_b\} \quad (1)$$

D_b is the definition regions of function $b(x, y)$. The *erosion* operation is:

$$(f \Theta b)(x,y) = \min\{f(x+x', y+y') - b(x',y') \mid (x',y') \in D_b\} \quad (2)$$

According to the two elementary mathematical morphology operations, we use the formula for image edge detection. Assuming $E(x, y)$ is the edge function of image, image edge detection operations can be constructed according to *dilation* operation as below:

$$E(x,y) = f(x,y) \oplus b(x,y) - f(x,y) \quad (3)$$

When the value of the gray *dilation* operation in structural element is positive, it will brighten the exported image, and reduce or eliminate the dark details. Therefore, the edge detection can be processing by formula 3. As a kind of mathematical morphology edge detection algorithm of nonlinear image process and analysis theory, it is simpler and more realizable. More details about pore image segment based on mathematical morphology can be seen in [3].

3. Maximum between-class variance algorithm based on area histogram

Otsu's algorithm works on a gray scale histogram and attempts to automatically separate a given image into foreground and background groups [4]. Obviously, it can be extended to obtain the optimal area threshold between pores and other closed regions.

Assuming $f(x, y)$ is the input image function of gray scale. All closed regions after image segmentation with mathematical morphology are sorted according to area, which was called area histogram. The sorted region with different area levels are denoted as $S = \{n_0, n_1, n_2, \cdots, n_{L-1}\}$, where L is the number of closed regions with different area levels, and n_i is the number of area levels in i. Threshold t divides all closed regions into two classes, C_0 with area $\{n_0, n_1, \cdots, n_t\}$ and C_1 with area $\{n_{t+1}, n_{t+2}, \cdots, n_{L-1}\}$, where C_1 represent pore and C_0 represent other cell structure except pore. Then, the closed region area probability distributions are:

$P_i = n_i / N, P_i \geq 0, \sum_{i=0}^{L-1} P_i = 1$, Where N is the total number of closed regions in image. P_i is probability of closed region level s_i. Then the probability C_0 and C_1 are

$$\omega_0 = \sum_{i=0}^{t} n_i / N = \sum_{i=0}^{t} P_i \quad (4)$$

$$\omega_1 = \sum_{i=t+1}^{L-1} n_i / N = \sum_{i=t+1}^{L-1} P_i = 1 - \omega_0 \quad (5)$$

Also, the means for classes C_0 and C_1 are

$$\mu_0 = \sum_{i=0}^{t} n_i * i / \sum_{i=0}^{t} n_i = \sum_{i=0}^{t} P_i * i / \omega_0 \quad (6)$$

$$\mu_1 = \sum_{i=t+1}^{L-1} n_i * i / \sum_{i=t+1}^{L-1} n_i = \sum_{i=t+1}^{L-1} P_i * i / \omega_1 \quad (7)$$

Let μ be the mean intensity for the all closed regions. It is easy to show that

$$\mu = \mu_0 * \omega_0 + \mu_1 * \omega_1 \quad (8)$$

We can define the between-class variance as:

$$\sigma^2 = \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2 = \omega_0\omega_1(\mu_0 - \mu_1)^2 \quad (9)$$

For bi-level thresholding problem, Otsu has verified that the optimal threshold t is chosen so that σ^2 is maximized. However, this method uses an exhaustive search to evaluate the criterion for maximizing the between-class variance. To determine the threshold of an image efficiently, we propose a modified between-class variance for this method.

4. Multi-objective GA-based thresholding algorithm

Genetic algorithm is classified as an efficient random search evolution algorithm that uses probability to guide its search. Thus the Otsu's drawback of being time consuming is overcome. Based on maximum between-class variance, we introduce second objective function about average area of closed regions to improve the pore segmentation performance.

4.1. Coding of individuals

Because all closed regions are sorted as { n_0, n_1, n_2, ⋯ , n_{L-1}}, it can be mapped into region { *0, 1, …, L-1*}, where L is the number of closed regions with different area levels. So the chromosome (individual) is encoded as *log*(L) bits strings, which represents a threshold of pore area.

4.2. Initialization

Initially we randomly generate some individuals to form an initial population. The population size N is preset. The populations generated randomly cover the entire range of possible solutions: from *0* to *L-1*. And each closed regions size has the same probability to be chosen.

4.3. Fitness function

For this problem, the first fitness function can be obtained by maximum between-class variance σ^2, according to formula 9. But single objective function usually disabled in perfect results. It can be verified by the experimentation below in section 5. So we introduce second objective function about average area of closed regions to improve the pore segmentation performance. This idea comes from the domain knowledge of wood science that is little proportion of pores in cross-sections. We use aggregation-based strategy, aggregate the objectives into a single parameterized objective e.g. weighted-sum aggregation. The aggregated fitness function shows in formula 11 as below.

$$F = a\sigma^2 + b\psi^2 = a\omega_0\omega_1(\mu_0 - \mu_1)^2 + b(\tau_0 - \tau_1)^2 \qquad (10)$$

Where τ_0 is the average area of the class C_0; and τ_1 is the average area of the class C_1. The two classes are divided by same threshold t with maximum between-class variance. The multi-objective optimal, that is maximum of σ^2 and minimum of ψ^2, can make the results of pore segmentation more excellent.

4.4. Selection

We use fitness proportionate selection, also known as roulette-wheel selection, for selecting potentially useful solutions for recombination. In this selection, the fitness function assigns a fitness for all possible solutions or chromosomes. Then the population is sorted by descending fitness values. Accumulated fitness values that are the sum of its own fitness value plus the fitness values of all the previous individuals are computed. Then a random number R between 0 and 1 is chosen. At last, the selected individual is the first one whose accumulated normalized value is greater than R. We can repeat above processes to acquire individuals $A_{11} \sim A_{N1}$ for reproduction. Meanwhile we use the strategy of elite reserved, which select maximum of fitness directly to next generation.

4.5. Crossover

In $A_{11} \sim A_{N1}$, a method of two-point crossover was used to produce new generations $A_{12} \sim A_{N2}$ by a probability of crossover. Everything between the two points is swapped between the parent organisms, rendering two child organisms.

4.6. Termination

This generational process is repeated until a termination condition has been reached, that is maximum iterations or the ratio of current generation average fitness to previous one is in [1.0, 1.005].

The individual that has the biggest fitness in the last generation is the optimal result.

5. Experiment Results

For evaluating the performance of our proposed method, six hardwood species images that have different kinds of wood are chosen. These are shown in Fig. 1. Algorithms are coded in Microsoft Visual C++ 6.0 and are run on an AMD Athlon 64 3000+ personal computer with 1G memory.

The computation time, thresholding, and number of pores for the nine tested images are listed in table 1. Parameters in genetic algorithm are: population size is

20, number of generation is 30, and probability of crossover is 0.9.

From table 1, the run times of multi-objective GA are larger than single-objective because of the extra spending of computing second objective function. But the thresholding obtained by multi-objective GA is smaller, so the more number of pores it gets.

Fig. 5 shows that single-objective GA has more effective to diffuse porous wood and solitary pore, see figure a and c, but many pores cannot be segmented for semi-diffuse porous wood, ring-porous wood or other pore combination except solitary pore, which can be found obviously e, f and g. Multi-objective GA method can improve the pore segmentation performance for all kinds of different wood. Because the second objective function can reduce the thresholding that acquire more pores from noises. From the effect of Fig. 1, it indicates that our proposed method can be used to segment the pores from cross-section images automatically.

6. Conclusions

Aiming for the problem of segmenting the pore feature automatically from cross-section images, this paper presents a new method based on the maximum between-class variance firstly.. Experiment shows the method has more effective to diffuse porous wood and pore solitary, but many pores cannot be segmented for semi-diffuse porous wood, ring-porous wood or other pore combination except solitary pore. So we take the domain knowledge of wood science as a second objective function about average area of closed regions.

Aggregation-based strategy is used in this paper. Comparison of experiment on six species with different kinds of pores demonstrates that the task of pore segmentation can be completed successfully for all kinds of hardwood by multi-objective function.

7. Acknowledgements

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8. References

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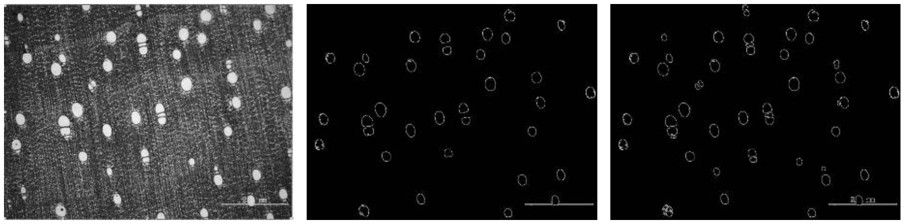
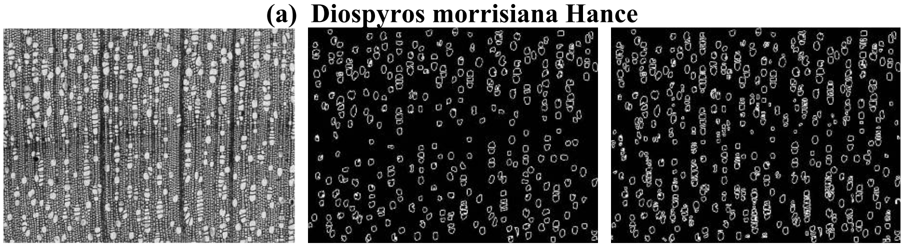
Appendix

Table 1. Contrast of two different algorithms

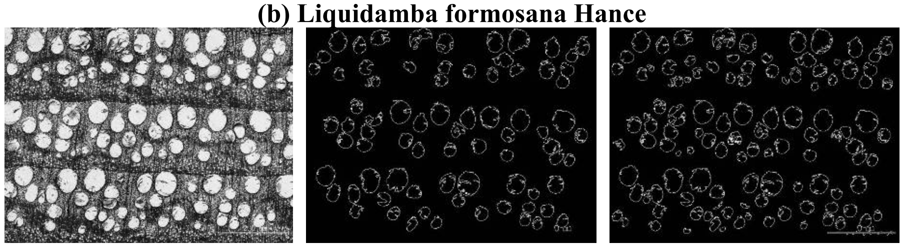
Species image	Single-objective GA			Multi-objective GA		
	Run times(ms)	Thresholding	Number of pores	Run times(ms)	Thresholding	Number of pores
a	406	6625	34	427	1392	52
b	47	513	332	56	172	536
c	1266	16037	76	1353	3319	122
d	281	3213	123	328	682	143
e	266	3437	292	312	922	485
f	483	13453	57	565	2256	112



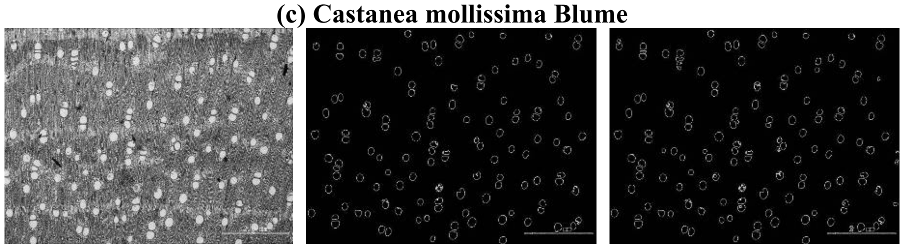
(a) Diospyros morrisiana Hance



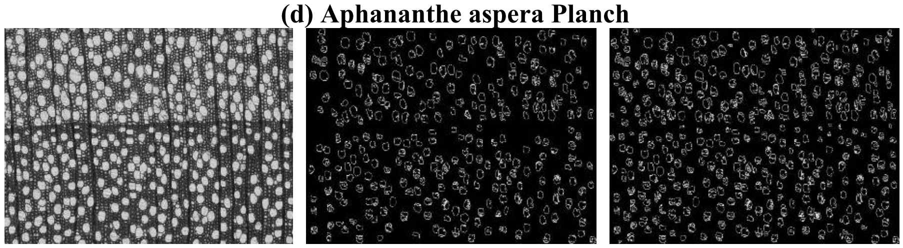
(b) Liquidamba formosana Hance



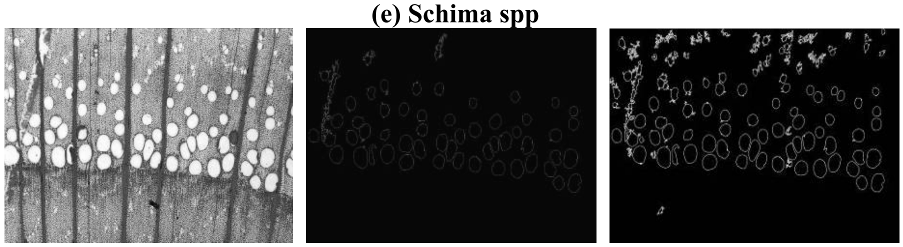
(c) Castanea mollissima Blume



(d) Aphananthe aspera Planch



(e) Schima spp



(f) Evodia fargesii Dode

Left column are original wood pictures, middle images are results processed by single-objective GA, and the right images are that of multi-objective GA.

Figure 1. Results of two methods