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Tree Image Segmentation Based on an Improved Two-Dimensional Otsu Algorithm

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Abstract

Influenced by light, houses, street lamps and other factors, tree images often contain noise and complex background information. The existing Otsu segmentation algorithms have deficiencies such as poor anti-noise capability, ignoring the class cohesion and so on. Based on the traditional gray value-neighborhood average gradient Otsu segmentation method, we propose an improved two-dimensional Otsu algorithm for tree image segmentation. The algorithm takes into account the between-class distance and within-class distance, which combined the average variance concept of two categories and proposed new threshold selection method, and reduce the interference of noise effectively. To achieve the best segmentation and reduce over-segmentation of background information, a method of removing small areas and morphological processing are used to optimize segmentation results. Experimental results show that the proposed algorithm has a good inhibition effect on noise and the effect of tree image segmentation is better than that of the traditional one.

***Keywords**: noise; two-dimensional Otsu; image segmentation; within-class distance*

1. Introduction

With the continuous development of image segmentation techniques, a series of studies based on precision forestry theories have emerged, Tree image segmentation provided important technical support for the stereoscopic measurements of trees characteristic, growth trend evaluation of trees, species identification and classification, and so on[1]. Tree images captured in natural scenes are quite easily disturbed by noise such as illumination and weather, simultaneously accompanied by house, street lamps, billboards and other complicated background information, which makes the work of tree images accurate segmentation particularly difficult[2]. As one of image segmentation methods, thresholding method occupies a very important position because of its simple calculation, running speed, high real-time performance and so on[3]. Wherein, Otsu method make the maximum degree of separation between target and background to be a segmentation criterion to achieve image segmentation[4]. However, this method only used the grayscale information on pixels without taking into account the spatial information on pixels, so the segmentation results are often unsatisfactory when the images have low signal-noise-ratio(SNR). For this reason, the literature [5] used the gray values of pixels and the average grayscale of its neighborhood pixels to constitute an Otsu method based on a two-dimensional (2D) histogram, the effect of segmentation improved obviously, but at the same time, the dimension of solution space increased so that the calculated amount increased and difficult to satisfy the requirements of real-time processing. In order to reduce the amount of calculation and shorten the running time, He Zhiyong *et al*.[6]

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proposed an algorithm which can search the Otsu threshold quickly, the algorithm overcame the disadvantages of exhaustive calculate between-class variance and increased the segmentation speed. Zhang Xinming *et al*.[7] used the gray-level distribution of 2D histogram to derive a new recursive algorithm to reduce the computational complexity. However, these methods were based on the 2D (grayscale and average grayscale) histogram[8], when they used a set of thresholds divide the 2D histogram into four rectangular areas, only along the diagonal of the two rectangular area participated in the calculation of the threshold but ignore the probability distribution of the two areas which located near the threshold vector and close to the diagonal line, the segmentation results obtained was not accurate enough. Literature [9] gives a grayscale - gradient 2D histogram and its region partition method to overcome the shortcomings of traditional 2D histogram, both segmentation effect and computing speed have clear advantages. The 2D Otsu method based on the grayscale and neighborhood average gradient which was proposed by literature [10] make the segmented intra-regional of image have better consistency, more accurate boundary shape, and better noise immunity. Although literature [9] and [10] had improved the effect of segmentation, the algorithm only considered the maximum between-class variance but ignore the class cohesion, which led to the background of the image segmentation is overmuch and the anti-noise performance is poor. Considering both the between-class distance and the within-class distance of the background and target, Literature [11] make the target and background of within-class distance within their respective average variance proportion changed according to the area ratio of target and background by adding weights, so that the threshold obtained is most close to the best threshold of the artificial selection.

On the basis of literature [10] and [11], this paper will address the shortcomings in the process of 2D Otsu image segmentation ,that the anti-noise performance is poor, the method ignore the class cohesion, segmented target existed much background information and others, we propose an improved 2D Otsu algorithm which take into account between-class distance and the within-class distance for color trees image segmentation, and optimize segmentation results by removing small areas, morphological processing and other methods, in order to achieve the best effect of tree segmentation.

2. 2D Otsu based on the Grayscale and Average Gradient

2.1. The Grayscale-Neighborhood Average Gradient Histogram

Let the size of an image $M \times N$, in which the range of gray value changes from 0 to $L-1$, and L is the number of grayscale. The neighborhood average gray level $g(x,y)$ of the pixel points located at (x,y) is defined as

$$g(x,y)=\frac{1}{N_D}\sum_{(x,y)\in D} f(x,y) \tag{1}$$

In where D generally takes the 8-neighborhood of pixel point (x,y), and N_D represents the total number of pixels in the neighborhood D.

The average gradient $\left|f(x,y)-g(x,y)\right|$ of pixel (x,y) is described in absolute difference between the gray value and its neighborhood average gray level. For an image, we define and calculate its 2D histogram when using representation as the form of vector$(f(x,y)=i,\left|f(x,y)-g(x,y)\right|=j)$. The histogram is defined in a square area with a size of $L\times L$, in which the horizontal expressed as the grey value of pixel and the ordinate expressed as the neighborhood average gradient of pixel, the value p_{ij} of any point of the histogram expressed as the joint probability density of vector (i, j) ,and is determined by the following formula

$$p_{ij} = \frac{c_{ij}}{M \times N} \tag{2}$$

Wherein $0 \le i, j \le L-1$, c_{ij} represents the number of times that (i, j) appears, and $\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij} = 1$.

$\{p_{ij}\}$ is the grayscale-neighborhood average gradient 2D histogram. Using the threshold vector (s,t) divide the 2D histogram into 4 rectangular regions shown in Figure 1. Among them, the pixel gray level of region 0 and the gray gradient are smaller, which indicates the target; the pixel gray level of region 1 is larger but the gray gradient is smaller, which indicates the background; the pixel gray level and gray gradient of region 2,3 are larger, which indicates the edge and noise. Compared with the grayscale-average grayscale histogram, the regional division of this histogram takes into account all the pixels of target and background as much as possible, improved the edges and noise problems in the target and background region of traditional histogram division, and make the segmentation results more accurate.

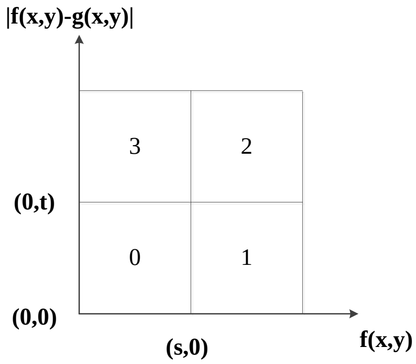

Figure1. Regional Division

2.2. 2D Otsu Algorithm based on the Grayscale-Neighborhood Average Gradient

When the segmentation threshold (s,t) is used to split an image, region 0 represents the target, and region 1 represents the background, then the occurring probability of region 0 and the occurring probability of region 1 are respectively as

$$\omega_0 = \omega_0(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} p_{ij} \tag{3}$$

$$\omega_1 = \omega_1(s,t) = \sum_{i=s+1}^{L-1}\sum_{j=0}^{t} p_{ij} \tag{4}$$

The mean vector of region 0 and the mean vector of region 1 are respectively as

$$\mu_0 = \mu_0(s,t) = (\mu_{0i}, \mu_{0j})^T = (\sum_{i=0}^{s}\sum_{j=0}^{t} ip_{ij} / \omega_0, \sum_{i=0}^{s}\sum_{j=0}^{t} jp_{ij} / \omega_0)^T \tag{5}$$

$$\mu_1 = \mu_1(s,t) = (\mu_{1i}, \mu_{1j})^T = (\sum_{i=s+1}^{L-1}\sum_{j=0}^{t} ip_{ij} / \omega_1, \sum_{i=s+1}^{L-1}\sum_{j=0}^{t} jp_{ij} / \omega_1)^T \tag{6}$$

The overall mean vector of the 2D histogram is given as

$$\mu_z = (\mu_{zi}, \mu_{zj})^T = (\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ip_{ij}, \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} jp_{ij})^T \tag{7}$$

Since it is assumed that all values are negligible in region 2 and region 3, we have

$$\omega_0 + \omega_1 \approx 1 \tag{8}$$

Define the discrete measure matrix σ_B of the target class and the background class as follows

$$\sigma_B = \omega_0[(\mu_0 - \mu_z)(\mu_0 - \mu_z)^T] + \omega_1[(\mu_1 - \mu_z)(\mu_1 - \mu_z)^T] \tag{9}$$

The trace of the matrix is used as the distance measure function between the target class and the background class, then

$$\begin{aligned} t_r\sigma_B(s,t) &= \omega_0[(\mu_{0i} - \mu_{zi})^2 + (\mu_{0j} - \mu_{zj})^2] + \\ &\quad \omega_1[(\mu_{1i} - \mu_{zi})^2 + (\mu_{1j} - \mu_{zj})^2] \\ &= \omega_0(s,t)\omega_1(s,t)[(\mu_{1i} - \mu_{0i})^2 + (\mu_{1j} - \mu_{0j})^2] \\ &= \frac{[\omega_0(s,t)\mu_{zi} - \mu_i(s,t)]^2 + [\omega_0(s,t)\mu_{zj} - \mu_j(s,t)]^2}{\omega_0(s,t)(1-\omega_0(s,t))} \end{aligned} \tag{10}$$

Formula(10), $\mu_i(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} ip_{ij}$, $\mu_j(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} jp_{ij}$.

We chose the threshold vector (s^*, t^*) which correspond to the maximum value of the distance measure function $t_r\sigma_B$ as the optimal threshold vector of the 2D maximum between-class variance threshold method, then

$$(s^*, t^*) = \arg \max_{0 \le (s,t) \le L-1} \{t_r\sigma_B(s,t)\} \tag{11}$$

Compared with the traditional 2D maximum between-class variance method, the results of this image segmentation algorithm have been greatly improved. However, the algorithm is only taking into account the maximum between-class distance, without considering the class cohesion. Consequently, this paper proposes an improved 2D Otsu threshold segmentation algorithm, which considers both between-class distance and within-class distance.

3. Improved 2D Otsu Threshold Segmentation Algorithm

In the image, the gray value of the interior pixel which located in the target region and the background region is generally uniform and the gray transition is smaller, so the distance between pixels within each class should be kept as small as possible. To this end, the 2D Otsu algorithm is improved to ensure maximum between-class distance, and also ensure the minimum within-class distance[12]. Yet, the within-class distance is smaller which means the class cohesion is better, relative to the target and background, the smaller the variance of their respective regions. As one of the uniformity measurement, average variance can directly reflect the uniformity of the image grayscale distribution, so we introduce the concept of two classes of average variance to measure the quality of cohesion, then

$$\overline{\sigma_0^2}(s,t) = \frac{1}{\omega_0(s,t)} \sum_{0 \le i \le s}\sum_{0 \le j \le t} [(i - \mu_{0i})^2 + (j - \mu_{0j})^2] p_{ij} \tag{12}$$

$$\overline{\sigma_1^2}(s,t) = \frac{1}{\omega_1(s,t)} \sum_{s+1 \le i \le L-1}\sum_{0 \le j \le t} [(i - \mu_{1i})^2 + (j - \mu_{1j})^2] p_{ij} \tag{13}$$

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Where, $\overline{\sigma_0}^2(s,t)$ represents the average variance of the target region, and $\overline{\sigma_1}^2(s,t)$ represents the average variance of the background region.

On this basis, a new threshold selection method is proposed, and the threshold calculation formula can be shown as follows

$$\begin{aligned} G(s,t) &= \frac{\omega_0\omega_1[(\mu_{1i}-\mu_{0i})^2+(\mu_{1j}-\mu_{0j})^2]}{\alpha\overline{\sigma_0}^2(s,t)+\beta\overline{\sigma_1}^2(s,t)} \\ &= \frac{[\omega_0\mu_{zi}-\mu_i(s,t)]^2+[\omega_0\mu_{zj}-\mu_j(s,t)]^2}{\omega_0(1-\omega_0)[\alpha\overline{\sigma_0}^2(s,t)+\beta\overline{\sigma_1}^2(s,t)]} \\ &= \frac{[\omega_0\mu_{zi}-\mu_i(s,t)]^2+[\omega_0\mu_{zj}-\mu_j(s,t)]^2}{\omega_0(1-\omega_0)[\sigma_0^2(s,t)+\sigma_1^2(s,t)]} \end{aligned} \tag{14}$$

Formula (14), α represents the occurring probability of the target region, that is $\omega_0(s,t)$, β represents the occurring probability of the background region, that is $\omega_1(s,t)$, $\sigma_0^2(s,t)=\sum_{0\le i\le s}\sum_{0\le j\le t}[(i-\mu_{0i})^2+(j-\mu_{0j})^2]p_{ij}$, $\sigma_1^2(s,t)=\sum_{s+1\le i\le L-1}\sum_{0\le j\le t}[(i-\mu_{1i})^2+(j-\mu_{1j})^2]p_{ij}$.

Due to the divided area ratio of target and background changing, and the general trend of uniformity measurement is also complementary, that is when the uniformity measurement of a region becomes larger, the uniformity measurement of another region will become smaller, so the sum of their average variance is not a constant. In order to reflect this complementary relationship, α and β are used as the weight coefficient to measure the proportion of average variance in the target and background.

From formula (14), we can see that the improved threshold selection formula use the ratio of the between-class variance and weighted within-class average variance as the selection criteria of the optimal threshold vector. When the between-class variance is the largest and the weighted within-class variance is the least, the effect of segmentation achieve the best. So when $G(s,t)$ takes the maximum value, the corresponding vector is the optimal threshold vector, which is

$$(s^*,t^*)=\arg\max_{0\le(s,t)\le L-1}\{G(s,t)\} \tag{15}$$

When the algorithm is used to calculate the threshold calculation formula, the arbitrary threshold vector (s,t) must be accumulated from $(1,1)$, which makes the calculation amount is extremely large. To improve the running speed, we need to recursive the five variables that is ω_0 , μ_i , μ_j , $\sigma_0^2(s,t)$ and $\sigma_1^2(s,t)$. Literature [10] has given the recurrence formulas of ω_0 , μ_i , μ_j variable as follows

$$\omega_0(s,t)=\omega_0(s,t-1)+\omega_0(s-1,t)-\omega_0(s-1,t-1)+p_{st} \tag{16}$$

$$\mu_i(s,t)=\mu_i(s,t-1)+\mu_i(s-1,t)-\mu_i(s-1,t-1)+s\cdot p_{st} \tag{17}$$

$$\mu_j(s,t)=\mu_j(s,t-1)+\mu_j(s-1,t)-\mu_j(s-1,t-1)+t\cdot p_{st} \tag{18}$$

According to the literature [13] recursive thinking, this paper recursive the $\sigma_0^2(s,t)$ and $\sigma_1^2(s,t)$ variables, which the recursive formulas are

$$
\begin{aligned}
\sigma_0{}^2(s,t) &= \sum_{0\le i\le s}\sum_{0\le j\le t}[(i-\frac{\mu_i}{\omega_0})^2+(j-\frac{\mu_j}{\omega_0})^2]p_{ij} \\
&= \sum_{0\le i\le s}\sum_{0\le j\le t-1}[(i-\frac{\mu_i}{\omega_0})^2+(j-\frac{\mu_j}{\omega_0})^2]p_{ij} + \\
&\quad \sum_{0\le i\le s}[(i-\frac{\mu_i}{\omega_0})^2+(t-\frac{\mu_j}{\omega_0})^2]p_{it} \\
&= \sigma_0{}^2(s,t-1)+\sum_{0\le i\le s-1}[(i-\frac{\mu_i}{\omega_0})^2+(t-\frac{\mu_j}{\omega_0})^2]p_{it} + \\
&\quad \left[(s-\frac{\mu_i}{\omega_0})^2+(t-\frac{\mu_j}{\omega_0})^2\right]\cdot p_{st} \\
&= \sigma_0{}^2(s,t-1)+\sum_{0\le i\le s-1}\sum_{0\le j\le t}[(i-\frac{\mu_i}{\omega_0})^2+(j-\frac{\mu_j}{\omega_0})^2]p_{ij} - \\
&\quad \sum_{0\le i\le s-1}\sum_{0\le j\le t-1}[(i-\frac{\mu_i}{\omega_0})^2+(j-\frac{\mu_j}{\omega_0})^2]p_{ij} + \\
&\quad \left[(s-\frac{\mu_i}{\omega_0})^2+(t-\frac{\mu_j}{\omega_0})^2\right]\cdot p_{st} \\
&= \sigma_0{}^2(s,t-1)+\sigma_0{}^2(s-1,t)-\sigma_0{}^2(s-1,t-1)+ \\
&\quad \left[(s-\frac{\mu_i}{\omega_0})^2+(t-\frac{\mu_j}{\omega_0})^2\right]\cdot p_{st}
\end{aligned} \tag{19}
$$

$$
\begin{aligned}
\sigma_1^2(s,t) &= \sum_{s+1\le i\le L-1}\sum_{0\le j\le t}[(i-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(j-\frac{\mu_{zj}-\mu_j}{\omega_1})^2]p_{ij} \\
&= \sum_{s+1\le i\le L-1}\sum_{0\le j\le t-1}[(i-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(j-\frac{\mu_{zj}-\mu_j}{\omega_1})^2]p_{ij} + \\
&\quad \sum_{s+1\le i\le L-1}[(i-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(t-\frac{\mu_{zj}-\mu_j}{\omega_1})^2]p_{it} \\
&= \sigma_1^2(s,t-1)+\sum_{s\le i\le L-1}[(i-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(t-\frac{\mu_{zj}-\mu_j}{\omega_1})^2]p_{it} \\
&\quad -\left[(s-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(t-\frac{\mu_{zj}-\mu_j}{\omega_1})^2\right]\cdot p_{st} \\
&= \sigma_1^2(s,t-1)+\sum_{s\le i\le L-1}\sum_{0\le j\le t}[(i-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(j-\frac{\mu_{zj}-\mu_j}{\omega_1})^2]p_{ij} \\
&\quad -\sum_{s\le i\le L-1}\sum_{0\le j\le t-1}[(i-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(j-\frac{\mu_{zj}-\mu_j}{\omega_1})^2]p_{ij} - \\
&\quad \left[(s-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(t-\frac{\mu_{zj}-\mu_j}{\omega_1})^2\right]\cdot p_{st} \\
&= \sigma_1^2(s,t-1)+\sigma_1^2(s-1,t)-\sigma_1^2(s-1,t-1)- \\
&\quad \left[(s-\frac{\mu_{zi}-\mu_i}{\omega_1})^2+(t-\frac{\mu_{zj}-\mu_j}{\omega_1})^2\right]\cdot p_{st}
\end{aligned} \tag{20}
$$

Compared to the traditional threshold selection method, although the improved 2D Otsu method has the same time complexity and both of them are $O(L^2)$, while it can not only consider the maximum between-class distance, but also take into account the minimum within-class distance. Obviously, it is more reasonable. The area ratio of target and background is changing actually, so the improved formula added to the weight coefficient when considering the within-class distance, making the average variance of target and background which in the within-class distance account for the proportion in

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accordance with the target and background in their size changes, the segmentation result is more accurate, and the specific algorithm flowchart as shown in Figure 2.

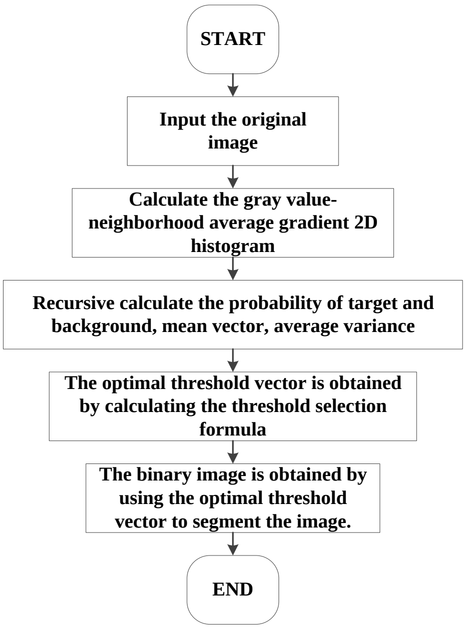


Figure 2. Algorithm Flowchart

4. Tree Image Segmentation Based on the Improved 2D Otsu Algorithm

The tree images captured in natural scenes are susceptible to the interference of illumination, weather and other noise, and there are buildings, street lamps, signs and other complex background information. Using the traditional 2D Otsu algorithm for image segmentation, the segmentation effect is not ideal, greatly influenced by noise. Therefore, this paper uses the improved 2D Otsu threshold selection algorithm for splitting the color tree images, optimize the segmentation results, which can reduce the impact of noise while obtaining the better segmentation results. The steps of tree image segmentation based on improved 2D Otsu algorithm are as follows

Step1: Get a few pictures of the color trees in the natural scene.

Step2: Image preprocessing. In order to verify the anti-noise performance of the algorithm proposed in this paper is better than the traditional threshold segmentation algorithm, adding noise points after gray the color image so that the effect of the contrast more vivid.

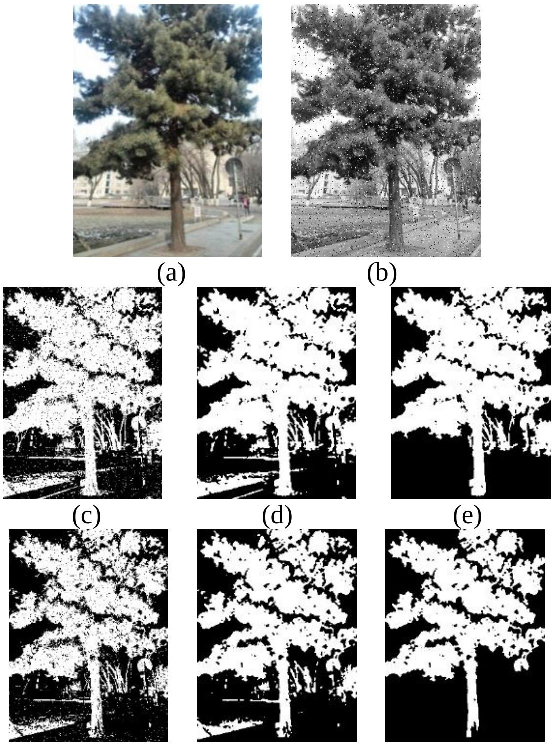
Step3: The improved Otsu algorithm which considers both between-class distance and within-class distance. The noisy gray tree image uses this algorithm for threshold segmentation so as to get a binary image.

Step4: Filtering process. The binary image after segmentation has noise and other interference, in order to do further optimization of the segmentation results, we need for image filtering.

Step5: Optimize segmentation results. To remove small connected areas, corrosion, expansion and other processing after the segmentation of the image to get the final result of the tree segmentation.

5. Experimental Results and Analysis

In order to validate the effectiveness of the improved 2D Otsu algorithm for color tree image segmentation, this paper compares the proposed algorithm with the algorithm of literature [10]. In the experiments, 4 color tree images of size 2448*3264 are shot by mobile phone, the size of the source images will be scaled to 240*320 in the treating process because of the too large images. In order to make the segmentation results of two algorithms compared more vivid, adding salt and pepper noise in the four images. The tests are conducted under the Windows 7 operating system, programming language for the MATLAB R2014a. The segmentation results of two algorithms are compared as shown in Figure 3-6.



(a) (b)
(c) (d) (e)
(f) (g) (h)

Figure 3. Tree Image 1 and Its Segmentation Results

(a) Color tree image 1. (b) Grayscale image with noise. (c) Segmentation result of image b by literature [10]. (d) Median filter image c. (e) Final result after optimize the image d. (f) Segmentation result of image b by the proposed method. (g) Median filter image f. (h) Final result after optimize the image g.

(a) (b)

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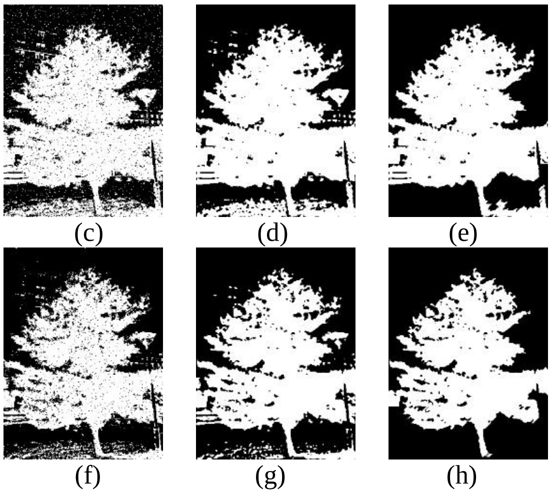

Figure 4. Tree Image 2 and Its Segmentation Results

(a) Color tree image 2. (b) Grayscale image with noise. (c) Segmentation result of image b by literature [10]. (d) Median filter image c. (e) Final result after optimize the image d. (f) Segmentation result of image b by the proposed method. (g) Median filter image f. (h) Final result after optimize the image g.

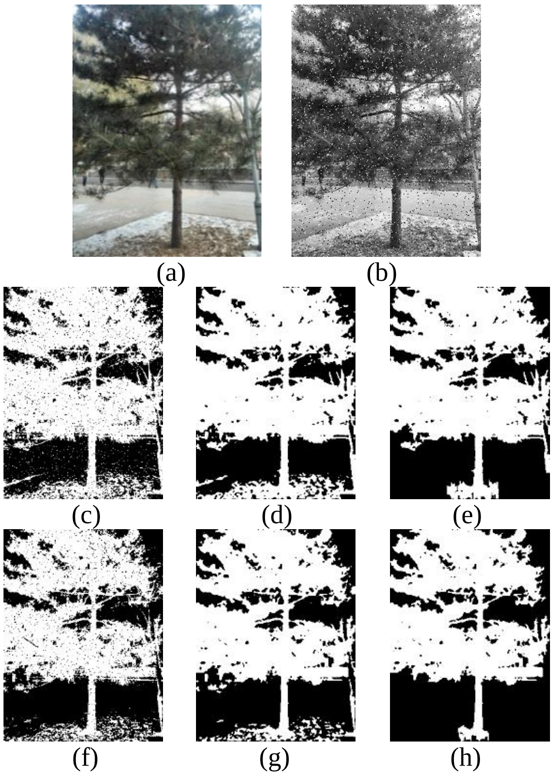

Figure 5. Tree Image 3 and its Segmentation Results

(a) Color tree image 3. (b) Grayscale image with noise. (c) Segmentation result of image b by literature [10]. (d) Median filter image c. (e) Final result after optimize the image d. (f) Segmentation result of image b by the proposed method. (g) Median filter image f. (h) Final result after optimize the image g.

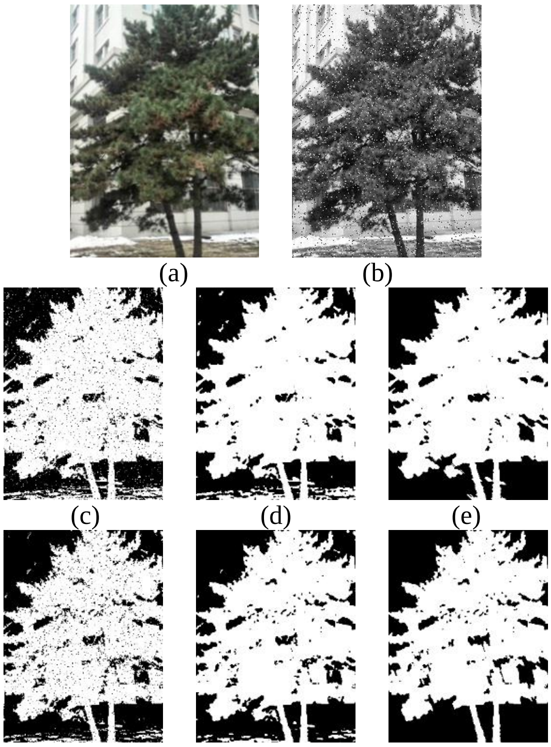
(a) (b) (c) (d) (e) (f) (g) (h)

Figure 6. Tree Image 4 and Its Segmentation Results

(a) Color tree image 4. (b) Grayscale image with noise. (c) Segmentation result of image b by literature [10]. (d) Median filter image c. (e) Final result after optimize the image d. (f) Segmentation result of image b by the proposed method. (g) Median filter image f. (h) Final result after optimize the image g.

Observing Carefully Figure 3 can be seen that the background portion and noise points are relatively more, despite median filtering Figure 3(c) to get the Figure 3(d), the noise points reduced greatly, but the optimized segmentation results Figure 3(e) can still see that there are many complex background information in the portion of the trunk. Compared with Figure 3(c), Figure 3(f) has a decrease in grassland section and better noise immunity. In Figure 3(g) can be clearly seen that the most of background information around the trunk separates from the truck, the segmentation results Figure 3(h) after optimization is better than Figure 3(e). From the original image of Figure 4 can be seen that exist some obstacles such as buildings and street lamps, due to the sunlight, the shadow of the trees appears beside the street. In this case, Figure 4(c) relative to Figure 4(f), the part of ground over-segmentation, while in Figure 4(f) the noise points are less than that in Figure 4(c), high segmentation accuracy, the optimized result from Figure 4(e) shows that shadows and lights are connected together, stairs and tree crown even together, didn’t separated with the trees, significant misclassification. While there is not too much ground and street lamps and other information in Figure 4(h), closer to the real images. From Figure 5 shows, obviously there is more noise in the segmentation results of literature [10] than that in the algorithm of this paper, the tree trunk is connected to the ground, which makes more over-segmentation, unsatisfactory results. Compared to the final optimal results, the segmentation result of the trunk in Figure 5(h) is slightly better than that in Figure 5(e). As can be seen from Figure 6, the algorithm in this paper has a strong inhibitory effect on noise, this is far superior to the algorithm of literature [10]. By contrast in Figure 6(e) and Figure 6(h) can be found that using the proposed algorithm in this paper to split the trunk is often more accurate.

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The algorithm in this paper considers both between-class variance and class cohesion, which has good practicability. Theoretically, since the proposed algorithm involves in the calculation of within-class mean variance, the amount of calculation increases, but its time complexity is the same as that of literature [10], are the $O(L^2)$ and the actual operation shows that this algorithm has minimal impact on the running speed.

6. Conclusions

In this paper, the study of color tree image segmentation algorithm, in view of the traditional algorithm based on grayscale-neighborhood average gradient has the problems, such as weak anti-noise performance, only consider the between-class distance but ignore the class cohesion. Combined with the mean variance, this paper proposes an improved Otsu threshold segmentation algorithm that taking into account the between-class distance and within-class distance for the color tree image segmentation, and through the optimization method to optimize the segmentation results to get the final results. Experimental results show that in the case of adding a lot of noise, compared with the traditional Otsu algorithm, this paper has stronger inhibitory effect on noise. Even though there is the complex background information in the image, this algorithm can also split out the trees well, and compared with the traditional algorithm, the final segmentation results of this algorithm are more close to the real situation. Consequently, whether from the effect of segmentation or the anti-noise performance to consider, compared with the traditional algorithm, this algorithm has distinct advantages.

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