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A New Image Segmentation Algorithm and Its Application in Lettuce Object Segmentation

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Abstrak

Segmentasi citra selada yang berdasarkan pengolahan citra komputer adalah premis dari pengujian kualitas selada non-destruktif. Algoritma entropi maksimum 2-D tradisional memiliki beberapa kesalahan, seperti akurasi segmentasi rendah, kecepatan lambat dan miskin kemampuan anti derau. Akibatnya, itu mengarah ke masalah segmentasi citra yang buruk dan efisiensi yang rendah. Suatu perbaikan algoritma entropi maksimum 2-D disajikan dalam makalah ini. Ini membagi daerah tersegmentasi dan lebih lanjut mengklasifikasikan pixel gambar tersegmentasi dengan metode entropi fuzzy minimum, dan mengurangi dampak titik derau, akibatnya akurasi segmentasi citra meningkat. Algoritma yang diperbaiki digunakan untuk segmentasi selada objek, dan hasil eksperimen menunjukkan bahwa peningkatan algoritma segmentasi memiliki banyak keunggulan dibandingkan dengan algoritma entropi maksimum 2-D tradisional, seperti berkurangnya interferensi palsu, kemampuan anti-derau yangkuat, ketahanan yang baik dan validitas .

Kata kunci: *entropi fuzzy maksimum yang rendah, entropi maksimum 2-D, kualitas selada, segmentasi gambar*

Abstract

Lettuce image segmentation which based on computer image processing is the premise of non-destructive testing of lettuce quality. The traditional 2-D maximum entropy algorithm has some faults, such as low accuracy of segmentation, slow speed, and poor anti-noise ability. As a result, it leads to the problems of poor image segmentation and low efficiency. An improved 2-D maximum entropy algorithm is presented in this paper. It redistricts segmented regions and furtherly classifies the segmented image pixels with the method of the minimum fuzzy entropy, and reduces the impact of noise points, as a result the image segmentation accuracy is improved. The improved algorithm is used to lettuce object segmentation, and the experimental results show that the improved segmentation algorithm has many advantages compared with the traditional 2-D maximum entropy algorithm, such as less false interference, strong anti-noise ability, good robustness and validity.

Keywords: *2-D maximum entropy, image segmentation, lettuce quality, minimum fuzzy entropy maximum*

1. Introduction

During the growth of lettuce, the disequilibrium of the moisture and nutrition can cause some problems, such as the rolled and yellow lettuce leaves, and the occurrence of sclerotinia sclerotiorum. In general, the diagnosis for moisture and nutritional elements is mainly based on laboratory routine testing [1]. However, there are some defects in this routine testing, such as the low test accuracy, the adverse influence on the growth of the lettuce, the poor timeliness, and needing a lot of manpower and material resources, so it is not beneficial to the promotion and application. Now,image technology and classification technique is used in many domains[2-3].Contrarily, the non-destructive testing that based on image processing technology has attracted widespread attention in the diagnosis of crop quality because of it is fast, convenient, non-destructive [4].

The effect of image segmentation directly affects the performance of the target recognition. Some common segmentation algorithms contain Otsu segmentation algorithm [5-7], genetic algorithm [8], fuzzy C-means segmentation algorithm [9, 10] and so on, but they also have certain limitations, for example, they only fit for the image which contains the fuzziness and the nondeterminacy, and they need much time for the calculation of the center pixel

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neighborhood.Documents [11-13] have provided some improvements for the traditional maximum entropy segmentation algorithm which has a range of shortcomings, such as the low calculation accuracy and the poor segmentation results, and they have acquired some good segmentation results. However, the two dimensional (2-D) maximum entropy algorithm assumes that the background region and object region occupy the most regions of the two-dimensional histogram, and it ignores the impact of the boundary region information on the segmentation results, so in many situations the segmentation effect is not good. For this problem, we re-divide the computational domain with the method of two-dimensional maximum entropy algorithm and re-classify the image pixels in the segmented images with the method of minimum fuzzy entropy, and then analyze its advantage through the experimental comparison.

2. Two Dimensional Maximum Entropy Segmentation Algorithm

Defining L as the image gray level, $a_0(x,y)$ as the gray value in point (x,y), $a_2(x,y)$ as the average gray value of the area which centre is the point of (x,y) and the neighborhood size is $k\times k$, the expression is shown as formula(1).

$$a_2(x,y)=\frac{1}{k^2}\sum_{m=-\frac{k}{2}}^{\frac{k}{2}}\sum_{n=-\frac{k}{2}}^{\frac{k}{2}}a_0(x+m,y+n) \tag{1}$$

In it, $1\le x+m\le M$, $1\le y+n\le N$. M and N are the width and the height of the image respectively. According to the value of K, K is set as 3,5,7,9 respectively in experiments, the experimental results show that k=3 is optimal, so k=3 is selected for subsequent experimental analysis [14]. In the calculation of $a_2(x,y)$, $a_0(x+m,y+n)$ is replaced by the boundary points when the $(x+m,y+n)$ exceeds the width and length of the image.

Defining the two-dimensional histogram Q (i,j) as the number of pixels whose gray value a0(x,y) is i and average gray value a2(x,y) of pixel neighborhood is j. In the size of M*N gray-scale image, the appearing frequency of two-tuples(i,j) is assumed as f_{ij},then the corresponding joint probability density pij is shown as formula(2).

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

Where $i,j=$0,1 …L-1, and $\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}p_{ij}=1$.

The entropy function expression of (i,j) is shown as formula(3).

$$\varphi(i,\mathrm{j})=\lg(\sum_{i=0}^{s}\sum_{j=0}^{t}P_{ij})+\frac{\sum_{i=0}^{s}\sum_{j=0}^{t}P_{ij}\lg P_{ij}}{\sum_{i=0}^{s}\sum_{j=0}^{t}P_{ij}}+\lg(\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1}P_{ij})+\frac{\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1}P_{ij}\lg P_{ij}}{\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1}P_{ij}} \tag{3}$$

Where the optimal threshold (s, t) is the value (i, j) when $\varphi(i,j)$ is the maximum.

3. Improved Segmentation Algorithm

Because the traditional 2-D maximum entropy segmentation algorithm does not take full account of the probability distribution of the threshold vector points within the region close to the diagonal, the accuracy of image segmentation is low, or the wrong segmentation will appear. Therefore, the paper proposes improvements on the traditional 2-D maximum entropy to compensate for its shortcomings. These improvements are as follows.

Firstly, the segmented region of the traditional 2-Dmaximum entropy segmentation algorithm is re-divided to contain more pixels which is close to the threshold.

Secondly, the membership function is structured, and reflects the extent of attribution of pixels to background or objectives. The image pixels of the initial segmented image are reclassified by the fuzzy minimum entropy algorithm.

3.1 Re-division of the segmented regions

Figure1 is a zoning map of the traditional image segmentation. The region is divided into four regions such as A, B, C and D. A and B are the effective areas, and C and D regions are ignored. However, Figure1 shows that part of the effective area which is close to the threshold point in the region B is ignored, so it will lead to low accuracy of image segmentation. For this problem, image segmentation area is redistricted in this paper, and the concrete methods is as below. Firstly, two straight lines which parallel the diagonal line are made and they intersect coordinate axis at (n, 0) and (0, m), then a line which is perpendicular to the diagonal line and cross the point(s,t) is made and it intersects the two parallel lines, so A1、B1、C1、D1 are the new regions and they can fully encompass the effective area near the diagonal line. The judgment domain division figure is shown as Figure 1.

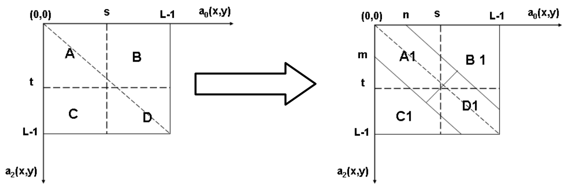

Figure 1. The judgment domain division figure

Figure1 shows that the dividing line of the background and objectives is perpendicular to the diagonal line and over the threshold segmentation vector point（s,t）, and the equation of the vertical line is shown as formula(4).

$$a_2(x,y)=-a_0(x,y)+s+t; \quad 0\le s,t<L-1 \tag{4}$$

A1 is the area surrounded by $a_2(x,y)\le -a_0(x,y)+s+t$ and $-m\le a_0(x,y)-a_2(x,y)<n$, and D1 is the area surrounded by $a_2(x,y)>-a_0(x,y)+s+t$ and $-m\le a_0(x,y)-a_2(x,y)<n$. A1 and D1 are the background and the target areas, and B1 and C1 are negligible, so the new threshold segmentation function is shown as formula(5).

$$Z(x,y)=\begin{cases} a_0(x,y) & a_2(x,y)+a_0(x,y)\le s+t\, and -m\le a_0(x,y)-a_2(x,y)<n \\ 0 & a_2(x,y)+a_0(x,y)>s+t\, and -m\le a_0(x,y)-a_2(x,y)<n \end{cases} \tag{5}$$

As can be seen from formula(5), the classification criteria of the functions $Z(x,y)$ is only relevant to the sum of s and t, and the sum of s and t can be used as a threshold value, so that the two-dimensional threshold will be converted into one-dimensional threshold. In addition, only the points in regions A1 and D1 are involved in the operation, so it can greatly improve the speed of operation. Compared with the traditional segmentation algorithm, this algorithm considers the probability distribution of the area near the diagonal line and close to the threshold vector point, and it also includes some points which have a large difference between pixel gray and gray-scale neighborhood average. These are all completed by the re-division of the region, and the points which probability is not zero can be included when m and n are taken the appropriate values. So this method can improve the efficiency of the segmentation and it is more universal.

3.2 Minimum fuzzy entropy classified processing

The useful information plays a great role in the correct segmentation of the image. In the segmentation algorithm shown in section 3.1, the values of m and n directly affect the segmentation results. If m and n are too small, the segmentation of some points will be missed. However, if m and n are too large, the large amount of computation must be needed. Therefore, the inappropriate selection of m and n will affect the segmentation results, and even lead to wrong segmentation. Based on the section 3.1, the pixels are reclassified by the minimum fuzzy entropy [15]. This method can improve the accuracy of segmentation furtherly, and the specific methods are as follows.

A. The construction of the membership function

We define the image which has been segmented by the segmentation algorithm mentioned in the section 3.1 as $Q=[q(x,y)]_{M\times N}$. In it, the window $W_k(i,j)$ is selected and the region size is k×k and the center is the point of (i, j), and k is odd. In order to reduce the computation and improve the segmentation speed, k is chosen as 3.

The gray values of the image Q which has been processed by the two-dimensional maximum entropy are 0 and 255. Then the gray value of background C0 is expressed as 0, and the one of objective C1 is expressed as 255. The two fuzzy sets Ic0 and Ic1 are defined by the window Wk(i,j) as the domain, and the equation of the membership function is shown as formula(6)and(7).

$$\mu_{co}(q(i+l_1,j+l_2))=\left[1+\left|q(i+l_1,j+l_2)-c0\right|\Big/c\right]^{-1};\ l_1,l_2=-1,0,1 \tag{6}$$

$$\mu_{c1}(q(i+l_1,j+l_2))=\left[1+\left|q(i+l_1,j+l_2)-c1\right|\Big/c\right]^{-1};\ l_1,l_2=-1,0,1 \tag{7}$$

Definition of the membership function is shown as formula(8).

$$e(A)=\frac{1}{n\ln 2}\sum_{i=1}^{n}S(\mu_A(X_i)) \tag{8}$$

$$S(\mu_A(X_i))=-\mu_A(X_i)\ln(\mu_A(X_i))-(1-\mu_A(X_i))\ln(1-\mu_A(X_i)) \tag{9}$$

B. The two fuzzy entropies of the two fuzzy sets are calculated

If the difference between a pixel and the values of its subordinate regional representation is smaller, the degree of membership from this pixel to the region is greater. To ensure the values of the formula (6) and formula (7) in [0.5, 1], the value of c is taken as 255. Thus the fuzzy entropy of the two fuzzy sets is shown as formula(10) and formula(11)

$$e(I_{c0})=-\frac{1}{(3\times 3)\ln 2}\sum_{l_1=-1}^{1}\sum_{l_2=-1}^{1}S(\mu_{c0}(q(i+l_1,j+l_2))) \tag{10}$$

$$e(I_{c1})=-\frac{1}{(3\times 3)\ln 2}\sum_{l_1=-1}^{1}\sum_{l_2=-1}^{1}S(\mu_{c1}(q(i+l_1,j+l_2))) \tag{11}$$

C. Re-classify the pixels in the segmented image

The two fuzzy entropy $e(I_{c0})$ and $e(I_{c1})$ are calculated for each pixel (x,y). If $e(I_{c0})<e(I_{c1})$, then q(i,j) =c0, else if $e(I_{c1})<e(I_{c0})$, q(i, j) =c1.This idea actually uses the regional information of the pixels in the window to realize (i,j) re-classification.

4. Experiment and Results

In the experiment, the color images of lettuce leaves are transformed into grayscale images firstly, and then the lettuce leaves object is splitted with the method of modified two-dimensional maximum entropy algorithm. At last, the segmented image is further processed by the method of fuzzy minimum entropy, and a part of the pixels are re-classified. At last, it can achieve the purpose of noise reduction. Figure.2 (a) and Figure.3 (a) are respectively the original gray-scale images of the lettuce. Figure.2 (b) and Figure.3 (b) respectively express the segmented images which have been processed by the two-dimensional maximum entropy. Figure.2(c) and Figure.3(c) respectively express the segmented images which have been processed by the two-dimensional maximum entropy after the re-division of the segmented regions. Figure.2 (d) and Figure.3 (d) are the images of the segmentation results which have been processed by the fuzzy minimum entropy. Figure.2(e) and Figure.3(e) are respectively the lettuce goal segmentation grayscales which are obtained by multiplying the pixels of the lettuce Images 2(a)、3(a) and the pixels of the two-dimensional maximum entropy segmentation images 2(b)、3(b), and Figure.2(f) and Figure.3(f) are respectively the segmentation grayscales which are obtained by multiplying the pixels of 2(a)、3(a) and the pixels of 2(c)、3(c) which have been processed by the two-dimensional maximum entropy after the re-division of the segmented regions. Figure.2(g) and Figure.3(g) are the segmentation grayscales which are obtained by multiplying the pixels of figure2(a)、3(a) and the pixels of figure2(d)、3(d) which have been processed by the fuzzy minimum entropy. According to the comparison of the experimental results, it can be drawn that the images marked by ‘1’, ‘3’, ‘5’ mistake the target portion of the lettuce images as the background, so the segmentation effect is poor. In this paper, the improved methods however can obtain the better segmentation effect. In the segmentation images processed by the improved algorithm , the effect of the images marked by ‘2’, ‘4’, ‘6’ is better than the images marked by ‘1’, ‘3’, and ‘5’. Therefore, the processing results on the lettuce image processed by the improved segmentation method are superior to the one processed by the traditional two-dimensional maximum entropy segmentation algorithm. The segmented images processed by the improved segmentation method have the advantages of the much more comprehensive valid information, the complete edge information and the good noise immunity.

Figure 2 (a) The original image

Figure 2 (b) 2-D maximum entropy Segmentation image

Figure 2 (c)The segmentation of the re-divided region

Figure 2 (d) The final Segmentation image

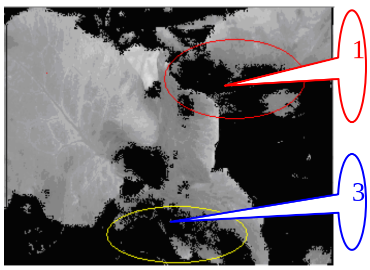

Figure 2 (e) 2-D maximum entropy segmentation effect image

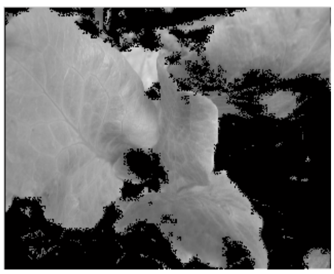

Figure 2 (f) The segmentation effect of the re-divided region

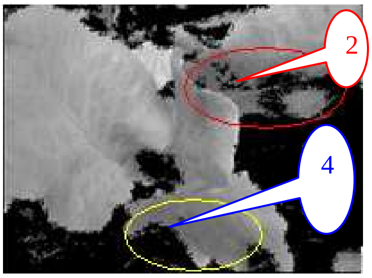

Figure 2 (g) The final segmentation Effect image

Figure 3 (a) The original image

Figure 3 (b) 2-D maximum entropy Segmentation image

Figure 3 (c) The segmentation image of the re-divided region

Figure 3 (d) The final Segmentation image

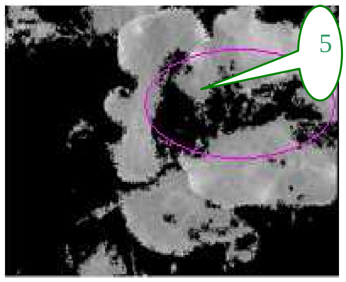

Figure 3 (e) 2-D maximum entropy segmentation effect image

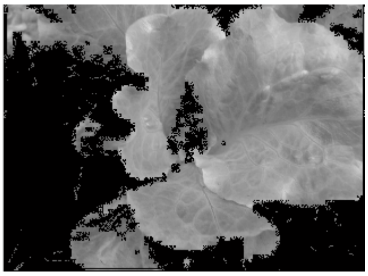

Figure 3 (f)The segmentation effect of the re-divided region

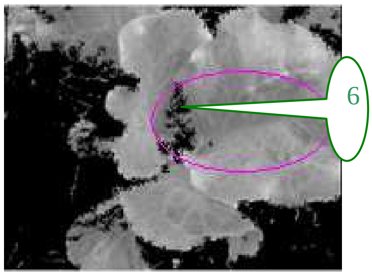

Figure 3 (g) The final segmentation effect image

In this paper, 2-D maximum entropy segmentation algorithm and the algorithm proposed in this paper are respectively used to segment the lettuce leaf 1 and the lettuce leaf 2, and the segmentation threshold values are shown in Table 1. The size of the initial images is 712*951.

Tab.1 Some experimental results

Segmentation algorithm	Lettuce image1 Threshold	Lettuce image2 Threshold
2-D maximum entropy segmentation algorithm	(98,98)	(105,100)
The algorithm proposed in this paper	(98,93)	(98,97)

The experimental environment is shown as below. The computer is chosen as HP Corporation, CPU is chosen as T43 dual-core Intel Pentium, and Memory has 2G storage. The processing software is chosen as matlab7.8.0.

5. Conclusion

In this paper, the improved segmentation algorithm is based on the 2-D maximum entropy segmentation algorithm and it is used to re-divide the segmentation region, and this method can make up the low segmentation accuracy and the poor noise immunity existing in traditional segmentation algorithm. Finally, the fuzzy minimum entropy is used to process the segmented lettuce image. The new method is superior to the traditional method in the segmentation effect. The new image segmentation algorithm has the advantages of the low false interference, the better noise immunity, the low classification error rate and the improved visual effects of the images. The success of the new algorithm can also provide a new methodological approach for the image target segmentation of other crops.

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