A PEST ACCURATE SEGMENTATION METHOD BASED ON CRITICAL POINT NONLINEAR ENHANCEMENT
/
基于临界点非线性增强的虫害精准分割方法

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ABSTRACT

The core of intelligent and accurate plant protection of pests is the accurate identification of pest monitoring and early warning model, and the quality of pest sample image is crucial to the model identification accuracy. To solve the problem of complicated background and low contrast colour image samples, in this paper it is proposed a pest accurate segmentation method based on critical point nonlinear enhancement. The segmented image is used as the sample image of the Faster R-CNN model, which can improve the accuracy of the recognition model. Firstly, the original image is segmented by a strong classifier and the image of pest cells with calibrated grids is obtained. Secondly, the Spline adjustment curve is fitted according to the core gray scale range and critical point, and the contrast between pest and mesh in pest monomer image is enhanced based on the Spline adjustment curve. Finally, there are some operations for the enhanced image such as threshold segmentation, contour extraction, morphological transformation and others to obtain the pest image without background interference, and some segmentation experiments are performed to the pest image based on different segmentation methods. The experimental results show that the proposed method can accurately segment the pests in complex background, and the comprehensive evaluation indexes such as recall ratio and precision rate are greater than or equal to 91.5%, which is better than the traditional segmentation method.

摘要

虫害智能精准植保的核心是虫害监测预警模型的精准识别，而虫害样本图像的质量是决定模型识别精度的关键。为解决其图像样本背景复杂、色彩对比度低等问题，本文提出一种基于临界点非线性增强的虫害精准分割方法。将分割后的图像作为 Faster R-CNN 模型的样本图像，提高识别模型精度。首先，使用强分类器对原始图像进行初步分割，获得含标定网格的虫害单体图像；其次，根据核心灰度范围与临界点拟合 Spline 调整曲线，将虫害单体图像基于 Spline 调整曲线增强虫体与网格的对比度。最后，对增强后的图像进行阈值分割、轮廓提取、形态学变换等操作，获得无背景干扰的虫害图像，并基于不同分割方法对虫害图像进行分割试验。试验结果表明：本文所提方法能在复杂背景中准确分割虫体，且查全率、查准率等综合评价指标均大于等于 91.5%，分割效果优于传统分割方法。

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INTRODUCTION

In the process of planting crops, they are susceptible to various pests. Insect pest has seriously threatened the yield and quality of agricultural products, and spraying pesticide is an important means of effective pest control. How to apply pesticides reasonably and avoiding overuse of pesticides have become an important research content to improve yield and quality (*GuoPing Wen, 2020*). It is a key measure for reducing pesticide waste to construct pest identification model, monitor and warn about pest and assist pesticide spraying. Traditional intelligent pest monitoring lamp can judge and monitor the insect situation by collecting the number and size of insects, but the types of insect pests cannot be accurately detected in this way. However, the monitoring and warning model based on Faster R-CNN can accurately monitor the type and quantity of insect pests. A large number of high-quality sample images without background interference are required to train this model. The quality and quantity of pest sample images directly affect the identification accuracy of the pest monitoring and warning model. At present, due to the lack of high-quality sample images, removing complex background interference and accurate segmentation are crucial to improving the quality of pest sample images. The images studied in this paper are collected by intelligent pest monitoring lamp. Since the traditional intelligent pest monitoring lamp judges the size of the insect body through the calibration grid, insect catching plate needs to be equipped with the calibration grid, which will reduce the image quality. The enterprise has arranged a large number of such equipment and acquired a large number of images. In order to solve the shortage of high-quality sample images in the training of pest model without updating the equipment, the algorithm in this paper starts from dealing with the existing images, and then amplify the pest image samples.

At present, traditional image segmentation methods include threshold segmentation, edge method, artificial neural network method, watershed method, etc. *Peng Huang et al, (2020*), and different segmentation methods adapt to different segmentation conditions. *Chenxi Liu et al, (2019),* segmented rice pests through improved level set algorithm*. Rong et al, (2022),* proposed a method for identifying and counting pests in field yellow plate based on Mask R-CNN, which solved the problem of inaccurate pest identification and counting by improving the feature pyramid network. *Guangqiang Diao, (2014),* segmented pests and diseases images through the study of Region of Interest detection and background segmentation. Scholars both at home and abroad have also conducted a series of studies on low-contrast image segmentation. In foreign countries, *Sarabpreet et al, (2016),* improved image contrast by combining multi-scale top cap filter and H-maximum value, and proposed a curve initialization level set method to extract the nucleus and cell boundary of contact cells. *Mohammad et al., (2018)*, improved the histogram segmentation technology and normalized the whole image to avoid the entropy loss in the process of image enhancement. In China, *Shuangxi Liu et al., (2016),* segmented corn grains dyed longitudinally through the multi-segment threshold segmentation method and obtained images of corn keratin endosperm and farinaceous endosperm. *Chenghui Han et al., (2018),* proposed a flame image enhancement and segmentation algorithm combining Retinex and CV (Chan-Vese) model, which accurately extracted low-contrast flame images in complex background environment and retained the irregular information of target edge.

The gray scale range of the insect body region extracted in this paper overlaps with the gray scale range of the calibrated grid region, resulting in low contrast. Traditional pest segmentation method has non-ideal segmentation effect. In terms of processing low contrast image, the image segmentation method based on deep learning is not ideal because of the lack of original samples. We often enhance its contrast firstly, and then segment it. So, in this article, we put forward a pest accurate segmentation method based on critical point nonlinear enhancement.

Contrast between insect region and calibration grid region is improved by non-linear enhancement method based on critical point, and complete insect pest image without accurate grid background can be extracted from complex background, which reduces the background grid interference to the shape feature extraction, finally the high quality sample image of insect pest is obtained. Thus, the precision of pest monitoring and early warning model is improved, which lays the application foundation for the research of intelligent spray and precise pesticide application.

MATERIALS AND METHODS

Acquisition and preprocessing of original images

The original image samples used in this paper are taken from the intelligent pest monitoring lamp developed by Jinan Xiangchen Technology Co., LTD. The whole machine structure is shown in Fig.1, which is mainly composed of light trap, industrial camera, electronic control unit and insect catching plate. Among them, the insect receiving plate adopts the background plate with calibration grid, which aims to facilitate the identification and calibration of pest sample size.

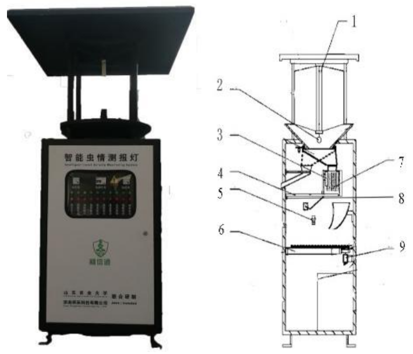


Fig.1 - The overall structure of intelligent pest monitoring lamp

1. Light trap; 2. sex induced core; 3. Insecticidal unit; 4. Electrically controlled turnover board; 5. Industrial camera; 6. Electronic control unit; 7. Oven; 8. Insect catching plate; 9. Driving mechanism

During operation, pests are trapped through light trap and sex induced core, the sex induced core contain insect pheromones. Firstly, pests fall into the pest control unit, and then after being dried in the oven, drop to the electrically controlled turnover board. The electronic control unit controls its turnover, and at the same time, the driving mechanism drives the insect catching plate to rotate, so that the pests randomly drop onto the insect catching plate. Industrial cameras collect pest photos, and upload them to the pest monitoring and early warning model through 5G module for monitoring and warning, which can assist in making pesticide application decisions. Among them, the industrial camera is MV-CE120-10GC plane array camera. The fixed lens is used to collect pest images during operation, with a resolution of 3264×2448.

Original image acquisition

Intelligent pest monitoring lamp has a fixed camera position, and the fixed light source and focal length are adopted to avoid the influence of illumination and sensor on the image gray scale. The images collected by intelligent pest monitoring lamp include the apple pests extracted in this paper: cutworms, cotton bollworm, armyworms, etc., as shown in Fig.2. As can be seen from Fig.2, the collected single photo contains complex background, calibration grid and multiple types of pest samples, and the pest samples are different in size, orientation, position and posture, with little difference in colour and calibration grid, and insects overlap.

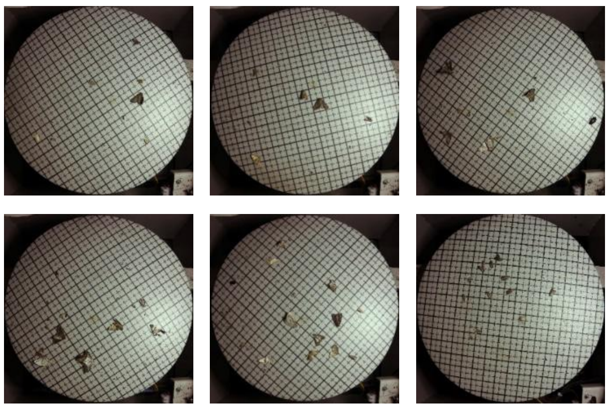
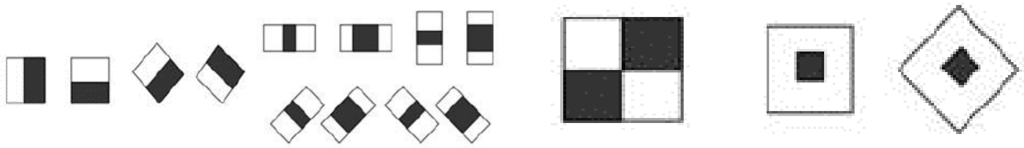


Fig. 2 - Original pest image

Initial Segmentation of Single Pest Image

A strong classifier is generated by Haar-like features and AdaBoost learning algorithm to initially segment single pest and single pest samples containing calibrated grids are obtained. Haar-like feature is a common feature descriptor in the field of computer vision. It is a digital image feature often used in object recognition. Haar-like feature value represents the gray level change of the image. By changing the position and size of the feature template, the image sub-window can list a large number of features to identify the target. As for pests' recognition and segmentation based on Haar-like feature, firstly, Haar-like feature extraction should be carried out on the image, and then the pest feature set and background feature set should be trained to establish a classifier. In order to take into account, the richness and recognition speed of feature sets, four types of Haar-like feature rectangles are set in this paper: A for edge feature, B for linear feature, C for central feature, and D for diagonal feature.



(a) Edge feature (b) Linear feature (c) Central feature (d) Diagonal feature

Fig. 3 - Haar-like feature rectangle

When extracting Haar-like features, the samples are normalized to the same scale of 24 * 24 pixels. Then, the number of Haar-like features is calculated according to Equations (1) ~ (3), and 51664 features are generated for each group of Class A feature rectangles, 28056 features for each group of Class B feature rectangles, 9985 features for each group of class C feature rectangles, and 37600 features for each group of Class D feature rectangles.

$$XY\left[W+1\text{-}w\frac{X+1}{2}\right]\left[H+1\text{-}h\frac{Y+1}{2}\right] \tag{1}$$

$$XY\left[W+1\text{-}z\frac{X+1}{2}\right]\left[H+1\text{-}z\frac{Y+1}{2}\right] \tag{2}$$

$$z=w+h \tag{3}$$

Where $W*H$ is the image size; $w*h$ is the characteristic size of rectangle; $X=["W"/"w"]$ is the maximum amplification scale coefficient of the rectangular feature in the horizontal direction; $Y=["H"/"h"]$ is the maximum amplification scale coefficient of the rectangular feature in the vertical direction.

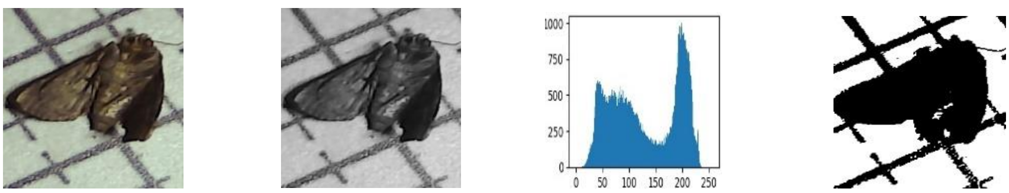
After the rectangular features being obtained, in order to improve the calculation speed and strengthen the real-time performance of the algorithm, the integral graph algorithm is introduced to calculate the eigenvalues so as to realize the rapid extraction of Haar-like features. The extracted Haar-like features are input into Adaboost to train and learn.

The Haar-like eigenvalues extracted from the samples to be identified are taken as the input of the strong classifier, and according to the weight of the eigenvalues, the strong classifier gives an evaluation value H to judge whether the samples are insects or not. If H=1, it indicates that the classification result is insect body, which will be segmented and extracted. If H=−1, the detected sample is not insect body. The original image is segmented based on the final generated strong classifier, and the results are shown in Fig.4. It can be seen from Fig.4 that the image after initial segmentation contains not only complete insects, but also the calibration grid, which affects the accuracy of the monitoring and warning model, so the calibration grid needs to be removed.

Fig. 4 - Single insect sample

Critical Point Nonlinear Enhancement

Taking the cutworms as an example, the image after initial segmentation is processed by grayscale processing, gray histogram extraction and watershed algorithm segmentation, and the image shown in Fig.5 is obtained.



(a) Original pest image (b) Grayscale image (c) Gray histogram (d) Watershed segmentation image

Fig. 5 - Original pest image, Grayscale image, Gray histogram, Watershed segmentation image

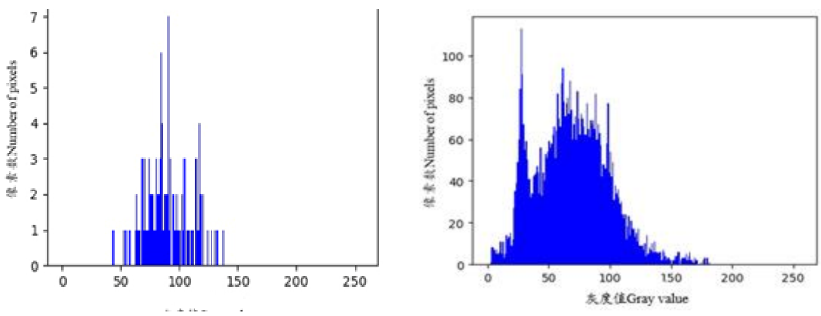
Among them, Fig. 5b is a gray image, Fig. 5c is a gray histogram, and Fig. 5d is a watershed algorithm segmentation diagram. As can be seen from Fig. 5c, in the pests gray histogram, the image has bimodal characteristics, and the pixel level of the valley bottom and the peak is significantly different. However, after being segmented by watershed algorithm, due to the low contrast between the calibration grid and the insect body, only the insect body and the calibration grid of the image can be separated with the background, but the insect body and the calibration grid cannot be separated. Therefore, a contrast enhancement method is needed to enhance the contrast between the calibration grid and the insect.

Core Grayscale Range Calculation

The nonlinear enhancement method based on critical point is to increase the dynamic range of gray value by nonlinear adjusting curve, so as to enhance image contrast. According to the gray histogram shown in Fig. 5C, the image gray value after initial segmentation is full of the whole dynamic range, so the image contrast cannot be improved solely by increasing the dynamic range of gray value. The core gray range contains a large number of pixels in the region to be enhanced, and the dynamic range of gray value is small.

Therefore, the dynamic range of gray value is compressed by processing pixels in the core gray range, and then the dynamic range of gray value is increased by nonlinear adjustment curve, finally, the contrast can be enhanced.

Histogram extraction is carried out for the grid region and the insect region respectively, and gray histogram of the grid region and the insect region are obtained as shown in Fig. 6. By analysing the distribution of pixels, it can be seen that pixels in the grid area and the insect area in the gray histogram are concentrated in the middle segment, while less pixels distribute at both ends, and the distribution law is similar to normal distribution. The core of gray level range of grid region and insect body region calculated by the probability density function of normal distribution are (30, 90), (45,130), respectively. Secondly, by gray overlap calculation, the both core grayscale level range is (45, 90). Finally, through nonlinear extension of core grayscale range, contrast between insect body area and calibration grid area is enhanced.



(a) Gray histogram of grid area *(b)* Gray histogram of insect region

Fig. 6 - Gray histogram of insect body and grid area

Critical Point Gray Value Calculation

The single method of nonlinear gray scale expansion for core gray scale cannot achieve the desired enhancement effect, which will result in weak enhancement or over-enhancement phenomenon. In terms of over-enhancement, the gray values of the pixels in the target area and the calibration grid area decrease at the same time, which will lose the features of the target object. However, in terms of weakly-enhancement, the weakening degree of the pixel value of the calibration grid area pixel cannot separate the target object from the background. As shown in Fig.7, threshold segmentation is performed on the enhanced images respectively. It is found that when over-enhancement occurs, however, leading to serious insect region loss at the same time. When weakly-enhancement occurs, the calibrated grid region cannot be separated from the insect region completely, as shown in Fig.8.

Fig. 7 - Over-enhanced image and its threshold segmentation diagram

Note: A1 is the over-enhanced image, and B1 is the threshold segmentation diagram of the over-enhanced image.

Fig. 8 - Weakly-enhanced image and its threshold segmentation diagram

Note: A2 is a weakly-enhanced image, and B2 is a threshold segmentation diagram of weakly-enhanced image.

In order to reduce weakly-enhancement, the gray value of critical point is required to be within the core gray value range. The nonlinear enhancement of image based on this critical point can maximize the enhancement degree of the insect region features and the suppression degree of the calibrated grid region features, and then achieve the best enhancement effect. In other words, when the gray value of the insect area is less than the critical gray value, the ratio of the total number of enhanced pixel points to the total number of pixel points in the insect region P is obtained; when the gray value of the insect area is greater than the critical gray value, the ratio of the total number of weakened pixel points to the total number of pixel points in the calibrated grid region P is obtained; It is required to maximize the average of P and Q, and the formula is:

$$X=\frac{P+Q}{2} \tag{4}$$

At the same time, in order to prevent over-enhancement in one of the regions and affect the enhancement effect, the critical point should lead to balanced enhancement of the insect region and the grid region, that is, the difference Y between P and Q is the minimum.

$$Y=|P-Q| \tag{5}$$

The comprehensive evaluation index Z is defined as the evaluation index of image enhancement. The larger the Z value is, the better the image enhancement effect is and the higher the contrast is:

$$Z=0.5X+0.5(1-Y) \tag{6}$$

By calculating the evaluation index of image enhancement, the maximum Z-value is 0.826 when the gray value is 80. The critical gray value is finally determined as 80, and its coordinate point in the curve adjustment function is (80, 80).

Spline Curve Fitting

The final Spline nonlinear adjustment curve is generated by Spline curve fitting the critical point coordinates (C, C), origin coordinates (0, 0), (a, 255), (b, 0) and the right-most coordinates of the curve (255, 0), where a is the minimum gray value of the core gray scale range, b is the maximum gray value of the core gray scale range, and c is the critical gray value. The non-linear adjustment curve of Spline is shown as follows:

$$S=\begin{cases} 0.00003\,r^4-0.0047r^3+0.1374r^2+6.7948r-10.623 & r<90 \\ 0 & r>90 \end{cases} \tag{7}$$

Where S is the gray value of pixel points after adjustment, r is the gray value of pixel points before adjustment.

After the image is enhanced by Spline adjustment curve, threshold segmentation is performed on the images before and after the enhancement respectively, as shown in Fig.9. It can be seen from Fig 9b and 9c that, after threshold segmentation of images enhanced by Spline adjustment curve, there is an obvious boundary between the insect area and the calibration grid, while there is no obvious boundary between the calibration grid and the insect of the image without adjustment curve enhancement.

(a) Enhanced image *(b) Threshold segmentation* *(c) Non-enhanced threshold segmentation*

Fig. 9 - Enhanced image and its threshold segmentation diagram and non-enhanced image threshold segmentation diagram

Accurate Segmentation of Pest Samples

In the process of different pest sample images, the core gray scale range and critical point of insect area and calibrated grid area are different due to the different gray scale range of insect area. Therefore, in order to achieve better segmentation effect, the gray values at the left and right ends of the core gray scale and critical point gray values should be calculated during the segmentation of different pests. The final Spline nonlinear adjustment curve is generated by Spline curve fitting through (0, 0), (a, 255), (c, c), (b, 0), (255, 0). Finally, the Spline nonlinear adjustment function is used to enhance the contrast between the insect region and the background region, and a high-contrast image is generated for subsequent segmentation.

Image enhancement is performed on the pest samples by nonlinear enhancement method based on the critical point, and threshold segmentation operation is performed on the nonlinear enhanced images and the unenhanced images at the same time. The results are shown in Fig.10. A1~A4 are the images enhanced by Spline nonlinear adjustment curve, B1~B4 are the threshold segmentation images enhanced by Spline nonlinear adjustment curve, and C1~C4 are the threshold segmentation images not enhanced by Spline nonlinear adjustment curve. By comparing B1~B4 with C1~C4, it can be found that, in the image B1~B4 through enhanced threshold segmentation, the pest region is separated from the calibration grid region, while in the image C1~C4 directly through the threshold segmentation, the calibration grid region is not separated from the pest region.

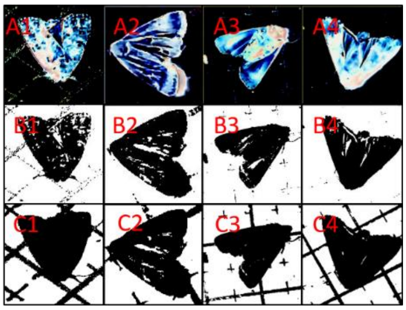


Fig. 10 - Image before and after enhancement and its threshold segmentation results

Note: The first row is a nonlinear enhanced image, and the second row is a threshold segmentation image of the first row. The third row image is the threshold segmentation image without nonlinear enhancement.

Due to different core gray scale range of each insect pest body, different segmentation functions should be created according to the pest species during the creation of segmentation model, that is, different Spline nonlinear adjustment curves should be established. In order to improve the applicability of the segmentation method and meet the requirements of accurate extraction of all kinds of pests, strong classifier will be used to classify the insect images, and different kinds of insect images will be separated by different segmentation models.

Accurate Extraction of Insect Body

The precise pest segmentation process based on critical point nonlinear enhancement is shown in Figure 11. Firstly, through Haar-like feature extraction and strong classifier generated by Adaboost, the pest monomer samples are segmented from the original image and the pest monomer image containing the calibrated grid is obtained. The segmented monomer pest images are classified according to species. Secondly, after being processed by each nonlinear adjustment function, each pest is processed by threshold segmentation. Through comparing the obtained image and the threshold segmentation result, it is found that binary image through piecewise nonlinear enhancement can separate insect body with the calibration grid, which is convenient for subsequent morphological processing. The image segmented by threshold still has a small number of noise interference points, so it is necessary to conduct contour statistics and the images are arranged according to contour size, and only the largest contour, namely the insect contour, is retained at last. For the noise interference inside the pest image, the cavity filling method is used to remove the interference and finally the complete pest binary image is obtained. Finally, the original image is combined with the binary image of insect pest to obtain the sample image only containing insect area. The background and calibration grid are completely removed to achieve accurate segmentation of pest samples.

Since the core gray scale range of each pest is different, different segmentation models should be built according to the pest species when establishing segmentation models, that is, different nonlinear Spline adjustment curves should be built according to the core gray scale range and critical points of images of different pests. In the process of insect extraction, strong classifier is used to preliminarily classify insect images, and the segmented insect monomer images are classified and screened according to species. Insect images of different species are separated by different segmentation models to improve the applicability of the segmentation method and meet the requirements of accurate extraction of various insect bodies.

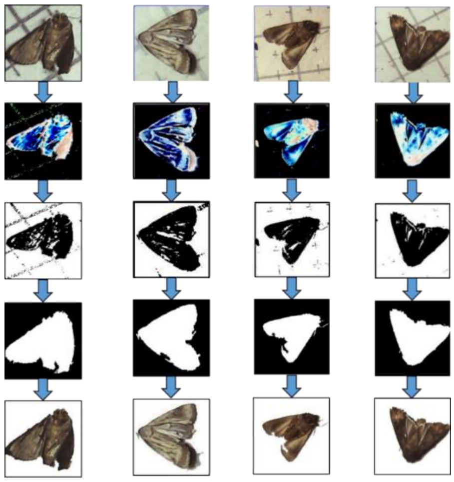


Fig. 11 -Segmentation flow chart

Note: from the top to the bottom, a single sample image Ai, a nonlinear enhancement image Bi, a threshold segmentation image Ci, a two-value image containing the insect contour Di, and no background image at all Ei and Fi (this method and manual segmentation), i=1÷6.

RESULTS

Test Design

In order to test the accuracy of the method proposed in this paper, manual segmentation is used as a reference standard to conduct comparative tests on the same pest image with different segmentation methods. Based on the method proposed in this paper, segmentation tests are carried out on different pest images, and then traditional segmentation methods such as Otsu threshold method, watershed method and regional growth method are used for segmentation tests on the same pest sample images, so as to compare and analyse the performance advantages of the proposed method in pest image segmentation.

Results of Pest Segmentation under Different Segmentation Methods

The proposed method is used to segment the images of 200 samples, including the main apple pests such as cutworms, cotton bollworm, armyworms, and common deer moth. In order to quantitatively evaluate the segmentation effect of pests, two indexes, global recall ratio (G_r) and global precision ratio (G_p), are introduced to evaluate the segmentation effect. Original image I is divided into N area, and its algorithm segmentation results are $M_{seg}=\{m^1_{seg},m^2_{seg},\cdots,m^N_{seg}\}$. The reference segmentation image is $H_{seg}=\{h^1_{seg},h^2_{seg},\cdots,h^N_{seg}\}$, and recall rate r is the area percentage of the overlap of the region m_{seg} obtained by this algorithm and the matching region h^m_{seg} in the reference segmentation region h^m_{seg}. The accuracy p is the area percentage of the overlapping part of the region m_{seg} obtained by segmentation in this paper and the matching region m_{seg} in the reference segmentation. The calculation formulas of recall rate, recall rate p, global recall rate G_r, global recall rate G_p, and comprehensive evaluation index F_1 are:

$$r_i=\frac{|m^i_{seg}\cap h^{m(i)}_{seg}|}{|h^{m(i)}_{seg}|}\times 100\% \tag{8}$$

$$p_i=\frac{|m^i_{seg}\cap h^{m(i)}_{seg}|}{|m^i_{seg}|}\times 100\% \tag{9}$$

$$Gr=\sum_{i=1}^{N} w_i \cdot r_i \tag{10}$$

$$Gp=\sum_{i=1}^{N} w_i \cdot p_i \tag{11}$$

$$F_1=2rp/(r+p) \tag{12}$$

Where m_{seg}^{i} is the i^{th} region segmented by the algorithm; $h_{seg}^{m(i)}$ is the matching region of the i^{th} region segmented by the algorithm in the reference segmentation graph; r_i is the recall ratio of region i; p_i is precision ratio of region I; w_i is the weighting coefficient, which is defined as:

$$w_i = \left|m_{seg}^{i}\right| / |I| \tag{13}$$

Recall ratio is an index to judge whether the segmentation result contains most features of the target region. The more features of target region the segmentation results contain, the higher recall ratio will be. Precision ratio is an index to judge whether the segmentation result can separate the target region from the background region. The less background features the segmentation results contain, the higher the precision ratio will be.

In order to further verify the advantages of the segmentation method in the segmentation of pest background in this paper, 200 pest sample images are taken as the research object, and different segmentation methods such as text method, Otsu threshold segmentation method, watershed method and regional growth method are used to segment the pest images. The results are shown in Fig.12.

Fig. 12 - Processing results of different segmentation methods

Note: A1 ~ A6, B1 ~ B6, C1 ~ C6, D1 ~ D6, E1 ~ E6 and F1 ~ F6 are the original drawing, Otsu threshold method, watershed method, regional growth method, this method and manual segmentation results respectively

In the pest image, the RGB colour of the insect body and the calibration grid is similar. When the Otsu threshold method is used to segment the image, the insect body region and the calibration grid region are seriously adhered, which makes it impossible to segment the insect body and the calibration grid. The watershed algorithm considers the insect region and the grid region as the same region, which can separate the calibration grid and the insect from the background, but cannot separate the calibration grid from the insect. The segmentation effect of the region growth-based segmentation method is basically the same as that of Otsu threshold segmentation method and watershed algorithm, which cannot separate the calibration grid from the insect. In terms of Otsu threshold method segmentation, although the pest area is extracted, it also mistakenly mistook the grid area with similar colour as the insect body, so the target image could not be accurately segmented. The final result obtained by the proposed method has a high similarity with the manual segmentation result, which can accurately segment the image with low contrast between the insect and the calibration grid, and the segmentation effect is more accurate than the traditional segmentation method.

In order to quantitatively evaluate the segmentation results of pest images processed by different segmentation methods, recall ratios, precision ratios and comprehensive index F_1 of pest images processed by different segmentation methods are counted respectively, and their average values are shown in Table 1.

Table 1

Quantitative evaluation of pest image segmentation results based on different segmentation methods

Evaluation index	Otsu threshold method	Watershed method	Regional growth method	Paper method
recall ratio	96.99%	92.24%	79.01%	93.21%
precision ratio	78.87%	86.31%	50.48%	91.74%
F1	87.93%	89.28%	64.74%	92.47%

Test Analysis

According to the analysis of the test data in Table 1, although the watershed algorithm has a high recall ratio and can separate the pest from the background, it cannot separate the calibrated grid from the pest, resulting in a low precision ratio. The F1 values of Otsu method and watershed algorithm are both below 90%, which could not separate the calibration grid from the pest. The accuracy of Otsu method is lower than that of the present method by 5.43% since the calibration grid area is regarded as the insect area. The recall ratio and precision ratio of the region growth method are very low, and it is impossible to separate the background from the pest. Traditional segmentation methods cannot segment the calibrated grid from the insect. The recall ratio, precision ratio and F1 value of the proposed method are all above 91%, which can separate the insect from the background and grid, and the segmentation effect is the best. Traditional segmentation methods can not accurately distinguish the low-contrast insect region from the calibrated grid region. The segmentation accuracy from low to high is region growth method, Otsu threshold segmentation method, watershed method, this method.

The above pest image segmentation experiments show that the method can accurately segment the pests and low contrast image. Different methods of pests and low contrast image segmentation results show that, the method for low contrast image, and the image with serious gray level range overlap between the target area and interference region, can enhance the contrast, and high contrast image is obtained. Its segmentation effect is superior to the traditional segmentation method with higher segmentation accuracy.

CONCLUSIONS

(1) In order to segment low-contrast insect image accurately, an image segmentation method based on critical point nonlinear enhancement method is proposed. Based on the core gray scale range and critical point, the nonlinear enhancement function is fitted by Spline function to realize the image enhancement of the insect region and the grid region. The enhanced image is processed by threshold segmentation to extract the insect image accurately.

(2) The segmentation effect of the proposed method is compared with that of the traditional segmentation method for low-contrast pest images. The results show that the recall ratio and the comprehensive index of the segmentation results obtained by the proposed method are both above 91%, which is the closest segmentation method to manual segmentation and has the best segmentation effect. Although the segmentation accuracy of region growth method, Otsu method and watershed method is improved successively, but none of them can accurately segment the insect and the background grid, and the final image still has grid interference.

(3) The pest images segmented by the method in this paper without background and grid can be used as the original samples for subsequent deep learning, which can greatly improve the accuracy of identification model, and contribute to subsequent pest identification research and provide high-quality raw materials for intelligent identification.

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