

SEGMENTATION OF RICE PLANTHOPPERS IN RICE FIELDS BASED ON AN IMPROVED LEVEL-SET APPROACH

基于改进水平集方法的农田稻飞虱图像分割

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ABSTRACT

With the wide application of machine-vision technology in detecting agricultural plant diseases and insect pests in the field, this paper proposed an innovative approach for performing automatic segmentation of rice planthopper images. First, to weaken background interference, the Otsu approach was adopted to accomplish the preliminary segmentation. Then, a steerable filter was employed to improve the segmentation results of the feet and tentacles. Finally, by adding priori gray-level information, our proposed method improved the approximation capability of level-set-based evolution curves to targets. Results indicated that the approach adopted in this paper could clearly segment the contour of rice planthoppers.

摘要

随着机器视觉技术在农业病虫害识别领域的广泛应用,基于图像的稻飞虱害虫诊断成为有效的手段,本文提出一个新颖的方法来完成稻飞虱的自动分割问题。首先,为了消弱背景干扰,利用大津法方法完成稻飞虱的初步分割。然后利用方向滤波器改善稻飞虱足和触角分割效果。最后融入先验灰度信息,提高了水平集演化曲线对于目标的逼近能力。结果表明,本文采用的方法可以清晰地分割稻飞虱的边缘轮廓,准确定位害虫区域。

INTRODUCTION

Rice planthoppers belong to Delphacidae, a kind of migratory pest that considerably damages rice. These planthoppers are the most serious pests of rice, and they inflict their harm by absorbing nutrients and releasing several destructive substances that substantially affect rice growth (Gurr et al, 2011; Matsukawa et al, 2014; Zhou et al, 2013). Rice planthoppers have about 200 species. The three most common species are the white-backed planthopper, the small brown rice planthopper, and the brown planthopper. Given the great harm caused by these rice planthoppers, agricultural producers usually misuse pesticides and consequently cause concealed problems in food safety. Thus, rice has been requested to be sprayed on-site at appropriate times and amounts, and real-time diagnosis has been proposed. However, considering their small size and dark colour, rice planthoppers are difficult to identify and distinguish from one another.

The approaches used locally and abroad for identifying rice planthoppers and other agricultural pests currently include acoustic detection, trapping, and near-infrared technology (Huynh et al, 2012; Selby et al, 2014). These methods essentially use manual detection. Normally, the recognition of infection depends on the inspector's practical experience. According to the current public literature, research on rice planthoppers has mainly focused on the relationship between the ecological environment and the insects' growth, as well as the prediction and forecast of future insect outbreaks (Bottrell et al, 2012; Li et al, 2013; Otuka et al, 2012). With the wide application of machine-vision technology in agricultural fields, image-based pest diagnosis is becoming a fast and effective approach. However, related literature on rice planthoppers is rarely available. Our team collects rice planthopper images taken from the field as samples and studies the insects in terms of identification, diagnosis, and prediction. Given the complex background information on the collected samples, image pre-treatment is required before image identification to remove irrelevant information, strengthen relevant information detectability, and maximally simplify the data. Consequently, the reliability of feature extraction and matching identification can be improved. Thus, as an important link for pre-treatment, the image segmentation of rice planthoppers directly affects the following feature extraction and identification links.

Research on machine vision technology began late in agriculture. Attaining a high-efficiency, high-accuracy segmentation algorithm is a hot and difficult issue in obtaining the automatic identification. In recent years, the level-set approach has been widely used in image segmentation because of its good segmentation results and theoretical basis. Chan and Vese combined the level-set theory with the Mumford-Shah (M-S) model and generated a C-V level-set model (Chan and Vese, 2001). This strategy adopted global information to extract target boundaries without relying on an image gradient. Therefore, images of no meaning to the gradient or those with weak edges can also be well segmented. At the same time, the improved algorithm (Allaire et al, 2014; Bashir et al, 2014; Li et al, 2005; Zhang et al, 2013) based on a C-V level set was achieved accordingly. Many improved level-set approaches demonstrate good performances in image segmentation. However, for cases with many complex images (e.g., background gray multilevel hierarchy), targets that are occluded or defected, and targets and background with similar gray levels, the segmentation results are hardly satisfactory without the support of priori information. Therefore, one important research direction for the level-set approach is to integrate targets' priori information into the level-set models and accordingly enhance the approximation capability of evolution curves to targets.

The remainder of this paper is organized as follows. Section 2 describes the traditional C-V level-set model and the main idea of an improved algorithm. Section 3 presents an actual experiment that evaluates the performance of the improved level-set approach. The conclusions are given in Section 4.

MATERIAL AND METHOD

The structure of the image acquisition device is designed based on the rice planthoppers' photo-axis feature of yellow and green. According to our preferences, 160 W self-ballasted fluorescent mercury lamps with high pressure are used as the background light source to trap rice planthoppers. A rice planthopper acquisition system is presented in Figure 1. Under the conditions of an open field environment, planthopper images are taken (Figure 2). The size of each captured image is 640 pixels by 480 pixels.



Fig.1 - Acquisition system of rice planthopper images

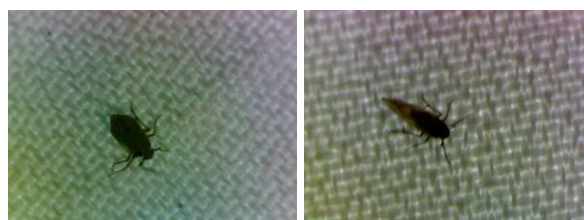


Fig.2 - Sample images of rice planthoppers

The C-V model assumes that the gray level of the homogeneous area is constant. The images are segmented into target area R_a (the average gray level is C_a) and background area R_b (the average gray level is C_b). The data smoothness item of the M-S models is removed, thus leaving the fidelity term and collective measurement item. The simplified fitting energy equation can be described as follows:

$$E(C) = E_a(C) + E_b(C) = \int_{\text{inside}(C)} |I - C_a|^2 dx dy + \int_{\text{outside}(C)} |I - C_b|^2 dx dy \quad (1)$$

In the process of curve evolution, Chan and Vese added length and area terms as bound terms and generated a general energy model for image segmentation as follows:

$$E(C, C_a, C_b) = \mu L(C) + \nu S_a(C) + \lambda_a \int_{\text{inside}(C)} |I - C_a|^2 dx dy + \lambda_b \int_{\text{outside}(C)} |I - C_b|^2 dx dy \quad (2)$$

In the formula, $\mu, \nu \geq 0$, $\lambda_a, \lambda_b > 0$ are the weight coefficients of each energy item, $L(C)$ is the length of evolving curve $C(x, y)$, and $S_a(C)$ is the acreage of the inner area. $L(C)$ and $S_a(C)$ are presented as follows:

$$L(C) = \int_{\Omega} |\nabla H(\phi(x, y))| dx dy = \int_{\Omega} \delta(\phi(x, y)) |\nabla H(\phi(x, y))| dx dy \quad (3)$$

$$S_a(C) = S[\text{inside}(C)] = \int_{\Omega} H(\phi(x, y)) dx dy \quad (4)$$

The C-V level-set model is based on the hypothesis of image piece-wise smooth functions. Therefore, the Heaviside and Dirac functions are introduced to cause the gradient descent flow equation to act at all level sets. As a result, the inner areas with hollow targets can be monitored automatically, and the energy function can be reduced to a global minimum. The discrete expression is:

$$H(z) = 0.5 \left[1 + \frac{2}{\pi} \arctan\left(\frac{z}{\varepsilon}\right) \right], \quad \delta(z) = \frac{d}{dz} H(z). \quad (5)$$

The abovementioned formula is then incorporated in equation (2) to yield the following energy function:

$$E(C, C_a, C_b) = \mu \int_{\Omega} \delta(\phi) |\nabla \phi| dx dy + \nu \int_{\Omega} H(\phi) dx dy + \lambda_a \int_{\Omega} |I - C_a|^2 H(\phi) dx dy + \lambda_b \int_{\Omega} |I - C_b|^2 [1 - H(\phi)] dx dy \quad (6)$$

After each iteration, the C_a and C_b values are expressed as:

$$C_a = \frac{\int_{\Omega} I(x, y) H(\phi(x, y)) dx dy}{\int_{\Omega} H(\phi(x, y)) dx dy}, \quad C_b = \frac{\int_{\Omega} I(x, y) [1 - H(\phi(x, y))] dx dy}{\int_{\Omega} [1 - H(\phi(x, y))] dx dy}. \quad (7)$$

On the basis of the variation approach, we combine equations (6) and (7) to generate the E-L expression of equation (2) as:

$$\frac{\partial \phi}{\partial t} = \delta(\phi) [\mu k - \nu - \lambda_a [I - C_a]^2 + \lambda_b [I - C_b]^2] \quad (8)$$

$$k = \frac{\phi_{xx} \phi_y^2 - 2\phi_x \phi_{xy} \phi_y + \phi_{yy} \phi_x^2}{(\phi_x + \phi_y)^{3/2}} \quad (9)$$

where k represents the curvature. According to the above analyses and results, the curve evolution status for each moment can be identified through numerical methods by only giving the level-set function of the initial time. The advantages of C-V models are shown in two aspects. First, targets with undefined edge gradient can be detected. Traditional edge detection methods not only lead to segmentation failure but also cause edge crack problems. Second, internal contours can also be detected automatically. Some problems are also found apart from favorable aspects. For example, the image with intensity inhomogeneity cannot be detected. The domain of the image function $I(x, y)$, which is involved in the PDF equation, concerns the entire image data with global features. Consequently, the calculation of data processing in the whole domain is considerably heavy.

The C-V level-set model uses global features to segment target images. Images are segmented into target area R_a and background area R_b to obtain the two-phase image segmentation. This strategy involves the use of same-level functions to segment two areas. In the natural environment, rice insect image acquisition in rice fields is degraded by uneven illumination. The corresponding gray-level histogram

contains two or more troughs, or the background image gray level contains two or more hierarchies. The two-phase image segmentation appears powerless. Therefore, rice planthopper images with similarities between targets and background or with intensity inhomogeneity cannot be effectively segmented by the C-V level set.

Accordingly, this paper considers two aspects to improve the C-V approach; initialization of the level-set function and priori information added to targets. In the traditional C-V approach, the level-set function is represented by a signed distance function generated from closed curves. Curve C divides the plane into internal and external areas. The signed distance function corresponds to $\phi(x, y) = \pm d$, where d represents the distance between point (x, y) and the curves on the plane. Normally, the signed distance function is defined as a circular conical surface, and the calculation is relatively complicated. In literature (Wei, 2010), the radius of the closed curve C is set to infinite; therefore, curve C can be shown as a straight line on the plane and divides the plane into the upper area $\Omega_u, y \geq y_0$ and lower area $\Omega_d, y < y_0$. The initialization function ϕ_0 is defined as a discontinuous curved surface function expressed as:

$$\phi_0(x, y) = \begin{cases} \rho_u, (x, y) \in \Omega_u \\ \rho_d, (x, y) \in \Omega_d \end{cases}, \rho_u \times \rho_d < 0 \quad (10)$$

Given the improved initialization of level-set functions, this paper employs the closed curve C in dividing the plane into internal and external areas (Ω_{in} and Ω_{out} , respectively), where ϕ_0 is defined as:

$$\phi_0(x, y) = \begin{cases} \rho_{in}, (x, y) \in \Omega_{in} \\ \rho_{out}, (x, y) \in \Omega_{out} \end{cases}, \rho_{in} \times \rho_{out} < 0 \quad (11)$$

Furthermore, the recalculation of values C_a and C_b is required after each iteration. The computational process costs a substantial period of time that still cannot guarantee the target image to be the segmentation result. Other background areas may also be included, and thus some considerable discrepancies between segmentation result and the target are attained in certain features. If rough priori information, such as the gray level, is already known, the tough gray level can be directly given to C_a and C_b . Thus, the computation during the whole iteration process can be greatly reduced, and the differences in the gray level feature between the segmentation result and the target can also be narrowed. This paper adopts this algorithm. C_a and C_b are known in the whole computation process, thus making the curve evolution alternately rely on the image target and background gray-level information.

The energy function of the modified C-V level-set segmentation model is as follows:

$$E(C) = E_0 + E_m(\phi) \quad (12)$$

where ϕ is the level-set function. Image similarity after segmentation is controlled by the first item E_0 on the right-hand side of the equation, which is used as the fidelity term. The specific form is:

$$E_0 = \lambda_a \int_{inside(C)} |I - C_a|^2 dx dy + \lambda_b \int_{outside(C)} |I - C_b|^2 dx dy \quad (13)$$

In the formula, $\lambda_a, \lambda_b \geq 0$. The second item $E_m(\phi)$ is the external energy term that prompts the evolution from the evolving curves to the target boundary. It is defined as follows:

$$E_m(\phi) = \mu L_g(\phi) + \nu A_g(\phi) \quad (14)$$

In the formula, $\mu, \nu \geq 0$ is the weight coefficient of each item. The definitions of $L_g(\phi)$ and $A_g(\phi)$ are:

$$L_g(\phi) = \iint_{\Omega} g \delta(\phi) |\nabla \phi| dx dy, A_g(\phi) = \iint_{\Omega} g H(-\phi) dx dy \quad (15)$$

where g is the edge indication function. The external energy term is added to obtain a more accurate contour of the segmentation target. The rough contour can be obtained through the effect of E_0 . For further refinement of the contour, we relied on the $E_m(\phi)$ item. Using the variation principle to achieve the minimum total energy equation (12), the E-L equation of the level-set function ϕ can be derived as

$$\frac{\partial \phi}{\partial t} = \delta(\phi) [-\lambda_a (I - C_a)^2 + \lambda_b (I - C_b)^2 + \mu(gk + \nabla g \frac{\nabla \phi}{|\nabla \phi|}) + \nu g] \quad (16)$$

RESULTS

The first strategy used determines a precise localization of the pest-infested area to adapt to the natural conditions in open rice fields. Otsu is an adaptive threshold determination method that is also called the maximum variance method. The basic concept of Otsu involves the use of a gray-level histogram to dynamically determine the image segmentation threshold based on the maximum variance between the target and the background. This method divides the image into the background and the target depending on the gray-level feature. The larger variance between the background and the target implies greater differences between the two parts of the image. Furthermore, the differences become smaller when part of the target is erroneously divided as the background or when part of the background is erroneously divided as the target. Using the Otsu method to apply image binarization to Figure 3 and eliminate small isolated areas through morphological operation, we obtain the rice planthopper binary image shown in Figure 4. The corresponding edge contour can be used as the initial contour of the level set.

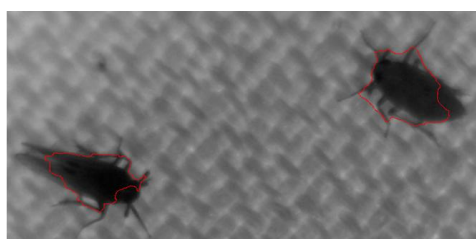


Fig.3 - Sample image of rice planthoppers



Fig.4 - Initial contour of the level set

In the experiment, the weight coefficient λ_a , λ_b , μ , and ν are all set to 1, time step Δt is set to 0.5, the function parameter ε of H is set to 1.5, ρ_{in} and ρ_{out} are set to 2 and -2, respectively. Through the analysis of a large number of plant diseases and insect pest images, C_a can be set to 55 and C_b can be set to 110. The segmentation results achieved by the traditional C-V and modified level sets are separately illustrated in Figures 5 and 6. The final images of the rice planthopper obtained by eliminating small isolated areas through the morphological operation of Figures 5(a) and 6(a) are shown as Figures 5(b) and 6(b). The intensity of non-homogeneity of the acquisition background (intensity inhomogeneity is mainly caused by curtain textures) caused the images with similarity between targets and background to be ineffectively segmented by the traditional level-set approach (Figure 5(b); the background region is divided into plant diseases and insect pest region). The algorithm proposed in this paper uses priori information to set up C_a and C_b of the target and the background and obtains better segmentation results than the traditional one. Figures 5(b) and 6(b) indicates that the algorithm also generates better performance in highlighting details.

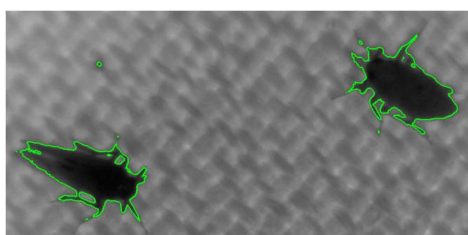


(a)



(b)

Fig.5- Segmentation result attained by the traditional C-V



(a)



(b)

Fig.6 - Segmentation result attained by the proposed C-V

To obtain good detailed segmentation, the feet and tentacles of the rice planthoppers must be enhanced before applying the contour evolution of the level set. The feet and tentacles of the rice planthoppers are not well segmented in the processing of insect pest image I (Figure 6(b)). In this paper, a steerable filter (Freeman and Adelson, 1991), which is a kind of directional gradient operator, is used to enhance the image. Through the linear combination of a group of basis filters, the filter achieves the response to any direction. The second derivative of a two-dimensional Gaussian function is used as the basis filter. The related expression is as follows:

$$G(x, y) = \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (17)$$

The corresponding second derivative is expressed by the following basis filter:

$$G_\theta(\sigma) = k_a(\theta)G_{2axy}(\sigma) + k_b(\theta)G_{2bxy}(\sigma) + k_c(\theta)G_{2cxy}(\sigma) \quad (18)$$

$$G_{2axy}(\sigma) = \left(\frac{x^2}{\sigma^2} - 1\right) \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), k_a(\theta) = \cos^2(\theta) \quad (19)$$

$$G_{2bxy}(\sigma) = \frac{xy}{\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), k_b(\theta) = -\sin(2\theta) \quad (20)$$

$$G_{2cxy}(\sigma) = \left(\frac{y^2}{\sigma^2} - 1\right) \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), k_c(\theta) = \sin^2(\theta) \quad (21)$$

where σ decides the scale of filters, and θ is the input direction. The decomposition angle θ of steerable filters can be set arbitrarily. For texture images, the angle at which the maximum variance of decomposition coefficient appears can be ascertained by increasing the decomposition angle from 0° to 180° by certain degrees. The result denotes that the texture images attain the most obvious gradient variation at such an angle. In the experiment, the direction angle is sampled as $0, \pi/N, \dots, (N-1)\pi/N$ to obtain many different directional filters. The value of parameter N is 18. We assume that plant disease and insect pest image H can be obtained after filtering image I to yield the following expression:

$$N(I) = \min(H, I) \quad (22)$$

The equation means that with the minimum pixel number of images I and H , $N(I)$ attains the evolution segmentation of a level set by replacing I . The results before and after filtering by steerable filters are displayed in Figure 7. The feet and tentacles of the rice planthoppers are enhanced with stronger contrast effects and more outstanding edges in Figure 7(b). The level-set segmentation result achieved using the approach proposed in this paper is illustrated in Figure 8. By comparing Figures 6(b) and 8(b), we note that the feet and tentacles of the rice planthoppers achieved better segmentation after direction filtering.

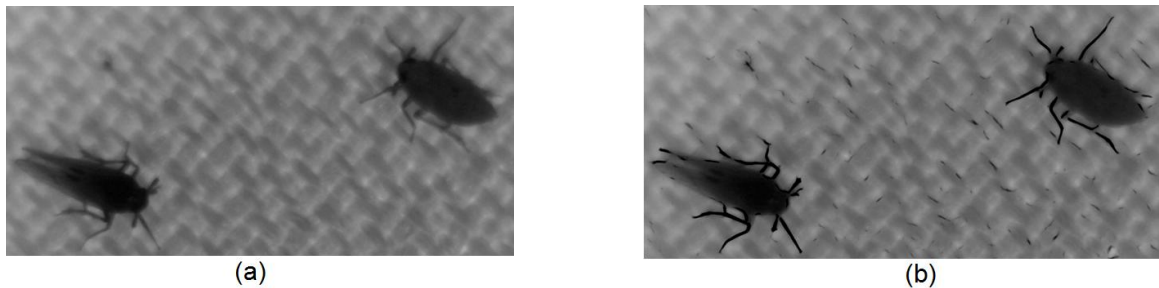


Fig.7 - Results before and after filtering by steerable filters

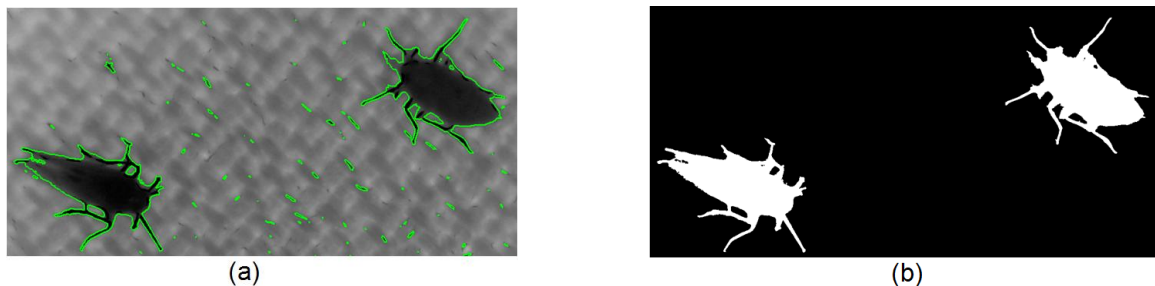


Fig.8 - Segment results of the proposed C-V after filtering by steerable filters

The comparison of the minimum iterative step and the iterative operation time is presented in Table 1. The hardware environment of this contrast experiment is a computer with a CPU Intel Core2 E7500+2.93 GHz and 1.96 GB memory. As shown in Table 1, the proposed method also exhibited significantly improved efficiency relative to the traditional C-V method.

Table 1

Comparison of different methods		
	Traditional method	Proposed method
Least number of iterations	263	4
Iteration time (ms)	807	312

CONCLUSIONS

The use of computer vision to recognize crop diseases has become a new development direction in precision agriculture. However, many disease and insect pest image segmentation algorithms are presently implemented in the laboratory environment. Under field conditions, the collected images of agricultural plant diseases and insect pests are more easily affected by noise, and thus a large number of false segmentations may occur. This paper discusses the improvement of image segmentation using the C-V level-set model from two aspects, namely, the initialization function and the target priori information. The study also reports an enhanced solution for the rice planthopper segmentation problem under open-field conditions. Using the proposed method, we further improved the segmentation results relative to those achieved by the traditional C-V level-set approach. This research also lays the foundation for succeeding feature extractions and identification. Rice planthoppers are a highly recognized natural disaster that considerably endangers rice production. Hence, multiple feature fusion of classification methods should be considered in future research to realize the remote real-time identification of the pest.

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