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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (20): 5859-5864, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.5859.5864

3D Reconstruction of Locust Based on Improved Chan-vese Model for Biological Education

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Abstract: The 3D reconstruction of infected locust is very important for the biological popular science education. Especially, the vector contour extraction of infected locust slice image is the key step in aspects of illuminating the interactive process between the locust organ and bio-pesticide. Some classic segmentation algorithms aren't suitable for the locust image with complex topology and minimal gray scale difference which will make the 3D reconstruction incomplete, inaccurate and non-vectorial. This study applies a new adaptive multiphase segmentation method of microscopic image based on improved Chan-Vese model to the 3D reconstruction. Firstly, in order to improve the speed and accuracy of contour extraction, the complex background is removed by scanning the pixel value in horizontal and vertical direction. And a great deal of isolated noises are reduced by the decision window. Secondly, the C-V model parameters $\lambda 1$, $\lambda 2$ and curvature are optimized by neglecting the curvature and setting the dynamical proportion of $\lambda 1$and $\lambda 2$. The exact extraction of tissue contour in the locust coelom has established a good foundation for the 3D reconstruction and organ deformation parameters calculation of coelom based on the above vector data.

Key words: Locust, 3D reconstruction, Chan-Vese model, adaptive multiphase segmentation

INTRODUCTION

The 3D reconstruction of infected locust is very important for the biological popular science education .But the traditional experiment bioassay methods exist some problems:1. Education experiment period is too long and data repeatability is poor. 2.The experiments are qualitative research rather than quantitative research. 3. The experiment data can't express the complicated neighbourship such as overlap of infected locust fully. The research has indicated that the biologic lesions detection (Wang and Chen, 2009; Zhang and Yan, 2000) and three-dimensional reconstruction (Vincent *et al.*, 2009; Ostadi *et al.*, 2009)are important morphological research method for serial tissue slice images.

The above method can be used to analysis the lesions of interacting tissues between locust organs and biologic pesticide, reappear the fine 3D structures of biologic tissues. The research method includes image acquisition, image denoising , image segmentation and 3D reconstruction, as shown in Fig.1. From Fig. 1, we can conclude that the image multiphase vector contour extraction is the important and key step of biologic lesions detection and three-dimensional reconstruction. The morphologic parameters' changes of infected locust tissue need to be considered at different infected time.

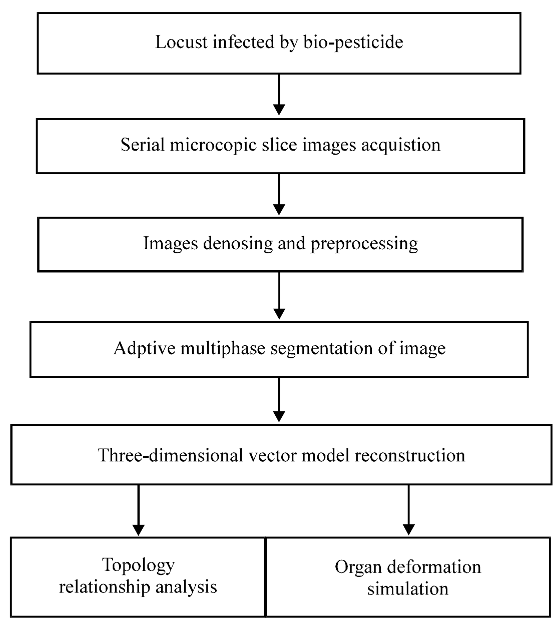

Fig. 1: Processing flow chart

The urgent problem is to extract the precise vector contours from two dimensional microscopic slice images. The study applies an adaptive multiphase segmentation method of microscopic image based on

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improved Chan-Vese model and pixel scanning background removal method to the 3D reconstruction.

LOCUST MICROSCOPIC IMAGE ACQUISITION

In the study, the oriental migratory locust and metarhizium biologic pesticide are obtained from the key lab for biocontrol of pests of ministry of agriculture, China Agricultural University. Firstly, the metarhizium biologic pesticide is inoculated into the locust in order to make it attack. Secondly, 0.5 um paraffin slices are prepared with LKB-3 ultramicrotome. The cutting direction is vertical to the long axis of the locust. Thirdly ,the slices are stained with uranyl acetate followed by lead citrate. Finally, they are observed with H-7500 microscopy and photographed. Taking the locust's coelom as example, as shown in Fig. 2. Obviously, the locust microscopic image is more complicated than general biologic images: 1. The gray scale difference is minimal and the fine cell tissue is easy to be regarded as noise. 2. The image boundary of locust' s soft tissues is blurry and the topology structure is very complex. 3. Especially many tissues are embedded each other. For the following 3D reconstruction, the extracted contours of many tissues should be closed, continuous and vectorial. The above image features of locust's coelom put forward austere challenge for the computational efficiency and accuracy of the contour extraction algorithm.

COMPLEX BACKGROUND REMOVAL AND IMAGE DENOISING

From Fig. 2, we can conclude that the background of biologic microscopic image is very complex, including microscopic field, blemish, isolated noise which will affect the velocity and accuracy of contour extraction. So the first step is to remove the microscopic field and reduce a great deal of noises. Especially, when the gray value of target image is close to the background image, the processing difficulty is concentrated on how to keep the entire contour of biologic tissue. In this study, a novel algorithm is proposed to resolve the above problem .The algorithm steps are as follows:

Step1: Scan the pixel value of microscopic image in horizontal direction. Compute the gray difference between every pixel and subsequent pixel. If the difference is less than threshold λ, the pixel gray value will be set as ε. And the pixel point will be regarded as boundary point

Step 2: Scan the pixel value of microscopic image in vertical direction. The calculation method is the same as it described in step1

Step 3: The two images obtained by step1 and step2 are made OR operation.Then the decision window is used to smooth isolated noise according to the area threshold method

Step 4: The background's gray value influences the speed of multiphase vector contour extraction and should be reset as approximating the coelom's gray value. So the background gray value of the image obtained by step 3 is reset as 192. The flow chart is shown in Fig. 3

The processing results of locust's coelom are shown in Fig. 4. The above results prove that the new algorithm can realize removing the image background (e.g.microscopic field, blemish, isolated noise, etc) and keeping the entire contour of biologic tissue which reduces redundant data and improves the speed and accuracy of image contour extraction greatly.

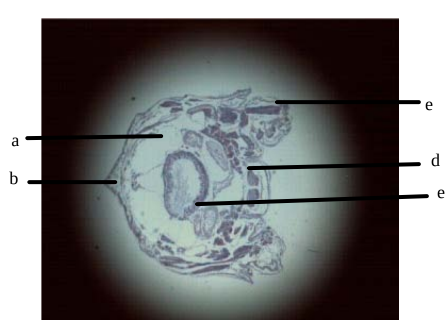

Fig. 2(a-e): Locust's coelom (a) pronotum (b) dorsal sinus (c) forestomach (d) muscle (e) foot

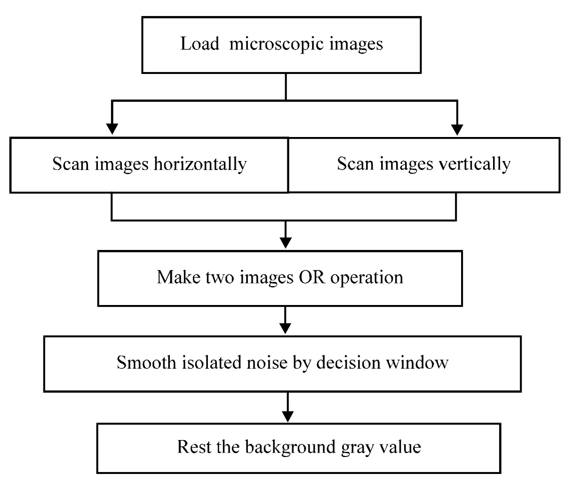

Fig. 3: Flow chart of image background removal and image denoising

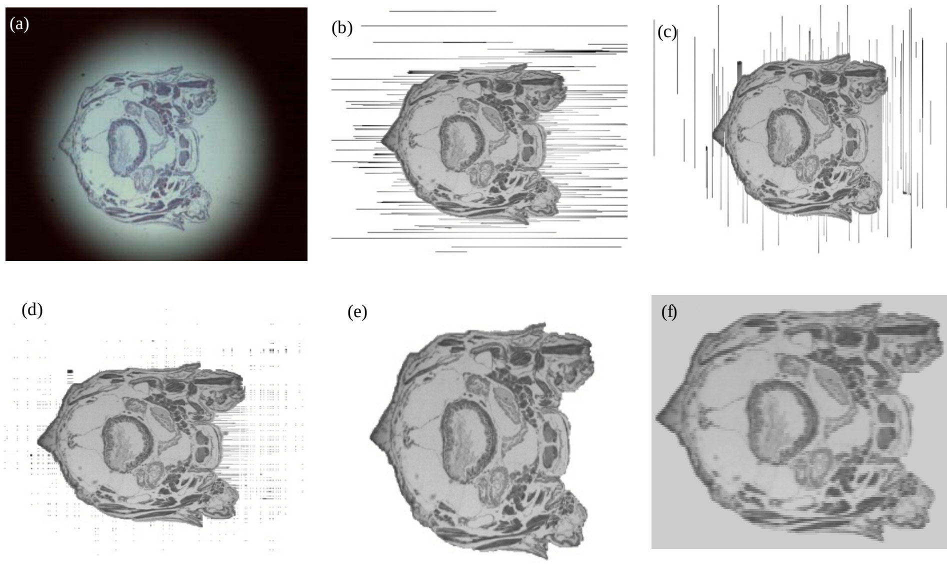

Fig. 4(a-f): Image background removal and denoising, (a) Origbal image, (b) Horizontal scanning, (c) Vertical scanning, (d) Or operation of (b) and (c) , (e) Inolated noise smoothing and (f) final result

ADAPTIVE MULTIPHASE SEGMENTATION METHOD BASED ON IMPROVED C-V MODEL

The classic image segmentation methods mainly include threshold segmentation, edge detection and region growing (Ji *et al*., 2007). The locust image processing results by threshold segmentation and edge detection are shown in Fig. 5. We can conclude that the extracted outline by interative optimal threshold is incomplete and non-vectorial. Using the region growing method,the seed points are very difficult to be selected artificially and the processing speed is very low. From Fig. 5 the positioning accuracy of edge detection method is not high and the continuous outline of complex gray-scale and detailed feature can't be extracted accurately. So the above segmentation algorithms aren't suitable for the locust image with embeded topology and minimal gray scale difference.

Image segmentation C-V model: The image processing technology based on partial differential equations can overcome the above difficulties to some extent and satisfy the need of accurate contour extraction (Wang and Xu, 2008) which can convert image segmentation problem into the solution of partial differential equation, such as active contour model.

The existing active contour models can be classified as parametric active contour model, geometric active contour model and regional active contour model according to representation and implementation. The geometric active contour model presents several advantages over the parametric active contours. Firstly, the contours represented by level set function may break or merge naturally during the evolution and the topological changes are thus automatically handled. Secondly, the level set function always remains a function on a fixed grid which allows efficient numerical schemes (Li *et al*., 2005). The geometric active contour models are based on curve evolution theory and level set method. The main idea is to represent contours as the zero level set of an implicit function defined in a higher dimension, usually referred as the level set function and to evolve the level set function according to a partial differential equation. In level set method, the key steps are the construction of initialization function ϕ_0 (x, y) and design

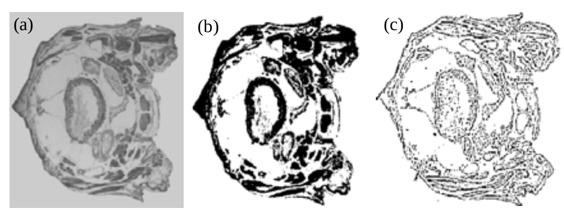

Fig. 5(a-c): Image background removal and denoising, (a) Initial image, (b) Interative optimal threshold and (c) edge detection of speed function. And the speed function often depends on image gradient and curve's curvature.

The Mumford-Shah model is an active contour model based on the region. Based on the theory of curve evolution, Mumford-Shah model and level set, the C-V model was be proposed by Chan and Vese (2001). The C-V model not only maintains the level set method's advantages of adaptive changes in topology but also is realized more easily and converges more rapidly. The main idea of the C-V model is as follows:

$$E^{CV}(c_1, c_2, C) = \lambda_1 \int_{\Omega 1} (I_0 - c_1)^2 \, dxdy + \lambda_2 \int_{\Omega 2} (I_0 - c_2)^2 dxdy + c|C| \quad (1)$$

$$c_i = \text{mean}_{\Omega}(u_0) = \frac{\int_{\Omega 1} u_0(x, y) dx\, dy}{\text{Area}(\Omega i)}, \ i = 1, 2 \quad (2)$$

where, $\lambda 1 > 0$, $\lambda 2 > 0$, I_0 is the image function. Suppose that the 2D image is divided into inner-boundary region Ω_1 and outer-boundary region Ω_2 by the closed boundary curve C. The average gray values of region Ω_1 and Ω_2 are represented as c_1 and c_2 respectively. The length of boundary curve C is represented as |C| and v is the corresponding weight coefficient. If the formulae is solved by level set method, the boundary curve C can be embedded into level set function□ (x, y), that is:

$$C = \{(x, y) | (x, y) \in \Omega, \phi(x, y) = 0\}$$

$$\Omega_1 = \{(x, y) | (x, y) \in \Omega, \phi(x, y) > 0\}$$

$$\Omega_2 = \{(x, y) | (x, y) \in \Omega, \phi(x, y) < 0\}$$

So the C-V model based on the level set can be defined as the following:

$$E(c1, c2, \phi) = \lambda_1 \int_{\Omega 1} | I_0 - c_1 |^2 H(\phi) \, dxdy + \lambda_2 \int_{\Omega} | I_0 - c_2 |^2 (1 - H(\phi)) \, dx\, dy + v \int_{\Omega} | H(\phi) | \, dx\, dy \quad (3)$$

Where:

$$H(\phi) = \begin{cases} 1, & \phi \geq 0 \\ 0, & \phi < 0 \end{cases}$$

The C-V model is solved by the variational method and the partial differential equation about is represented as the following:

$$\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi)[c\,\text{div}(\frac{\nabla \phi}{\nabla \phi}) - \lambda_1 | I_0 - c_1 |^2 + \lambda_2 | I_0 - c_2 |^2] \quad (4)$$

where, div((∇∅)/|∇∅|)is the curve of level set function ∅. δe (ϕ) can inhibit the too quick growth of level set function. The level set function ϕ (x, y, t) at time t is obtained which is a space surface. Let (x, y, t) = 0 , the obtained contour is named as zero level set, that is the target boundary curve.

Parameter optimization of C-V model: In this section, the parameters of equation (4) are optimized, including level set curvature, λ_1, λ_2, c_1 and c_2. By analyzing the correlation of above parameters, the target controllable segmentation is realized. The work mainly includes three parts.

In the above nonlinear PDE , the function of level set curvature is to keep the smoothness of the boundary. During the evolution process of boundary curve, the function of level set curvature is only auxiliary. In order to discuss these parameters conveniently, neglect the curvature and let v = 0. The simplified model can be defined as the following from the above equation 4.
The simplifying processing can improve the image segmentation speed effectively:

$$\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi)[-\lambda_1 | I_0 - c_1 |^2 + \lambda_2 | I_0 - c_2 |^2] \quad (5)$$

During the evolution process of boundary curve, the average gray values c_1 and c_2 of internal and external boundary will change accordingly. When the evolution curve of zero level set is consistent with the target boundary , the evolution curve will stop and the values of c_1 and c_2 will approach constant, that is $(\partial \varnothing)\, \partial t \to 0$. So the equation (6) is deduced in this study as the following:

$$\frac{\lambda_1}{\lambda_2} = \frac{| I_0 - c_2 |^2}{| I_0 - c_1 |^2} \quad (6)$$

At present ,the parameters $_{\varepsilon 1}$and $_{\varepsilon 2}$ are usually taken as constant, that is $\lambda 1 = \lambda 2 = 1$. So the adaptive multiphase segmentation is very difficult to be realized. In this study, we will control the gray values c_1 and c_2 by setting the proportion of $\lambda 1$ and $\lambda 2$ to realize segmenting the target adaptively and accurately. Set $k = \lambda_1/\lambda_2$ Introduce the parameter *k* into the equation (5). Solving functional extremum means the end of image segmentation.

Therefore, the segmented target can be selected actively by adjusting the vaule of λ_1/λ_2 . Even if the image includes multiple targets, the gray value of awaiting segmentation target only needs to be assigned to c_1 , the gray value of other targets and background is assigned to c_2. By the iterative solution of equation, the value of λ_1/λ_2 is defined as the following:

$$\frac{\lambda_1}{\lambda_2} = \left(\frac{(c_1)}{(c_1 - c_1)} \right)^2 \quad (7)$$

\3D reconstruction of locust: In the section , we apply the improved C-V model to extract the multiphase geometric features of locust coelom microscopic image adaptively and reconstrut the 3D model of coelom. The locust coelom image is expressed as Fig. 4 with the resolution of 700×700. The main organs include pronotum, dorsal sinus, forestomach, muscle and foot. After the metarhiziums invade locust's coelom and begin to reproduce, the organs will be deformed obviously. For example, the muscle will become loose and the forestomach will be gradually thinned.

The image edge is in crenation pattern and falls into depth depression which is difficult for extracting the multiphase tissue. We adopt the dynamic value of λ_1/λ_2 and realize the adaptive multiphase segmentation of locust microscopic image based on the single level set function. The processing results are as following.

From Fig. 6 , the multiple embedded vector contours are extracted and the contour feature points can be recorded. We can compute the position, circumference ,area , shape factor of each tissue by these feature points, as shown in Fig.7a .The exact extraction of tissue contour in the locust coelom will establish a good foundation for the 3D reconstruction and deformation parameters calculation of coelom based on the vector data, as show in Fig. 7b, c.

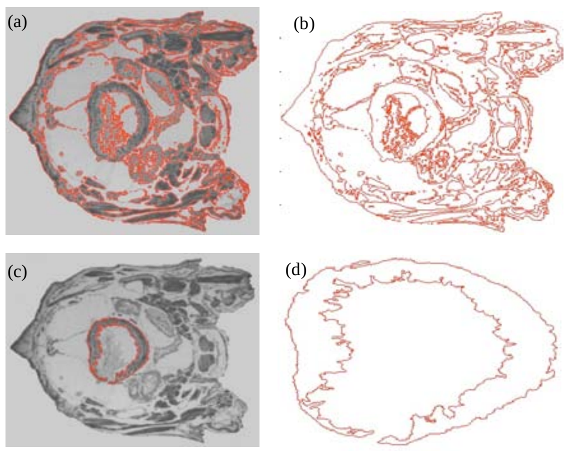

Fig. 6(a-d): Adaptive multiphase segmentation of locust microscopic image, (a) Closed and embedded vector contour, (b) Vector contour graph of locust coelom, (c)Vector contour of forestomach and (d) Vector contour graph of forestomach

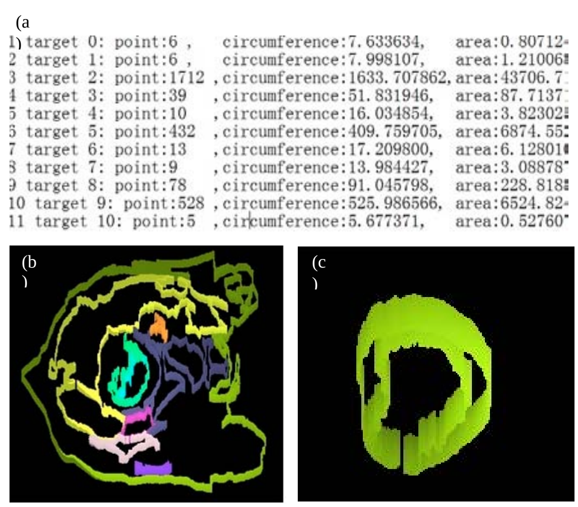

Fig.7(a-c): Geometric features calculation and 3D reconstruction of some locust tissues, (a) geometric features calculation of locust coelom, (b) 3D top view of locust coelom and (c) The 3D side view of forestomach

CONCLUSION

The 3D reconstruction of infected locust is very important for the biological popular science education. Especially, the vector contour extraction of infected locust slice image is the key step in aspects of illuminating the interactive process between the locust organ and bio-pesticide. The study applies a new adaptive multiphase segmentation method of microscopic image based on improved Chan-Vese model to the 3D reconstruction. Firstly, in order to improve the speed and accuracy of contour extraction, the complex background is removed by scanning the pixel value in horizontal and vertical direction. And a great deal of isolated noises are reduced by the decision window. Secondly, the C-V model parameters $\lambda 1$, $\lambda 2$ and curvature are optimized by neglecting the curvature and setting the dynamical proportion of $\lambda 1$ and $\lambda 2$. The experimental results show that the exact extraction of tissue contour in the locust coelom has established a good foundation for the 3D reconstruction and organ deformation parameters calculation of coelom based on the above vector data.

ACKNOWLEDGMENTS

We would like to thank to the reviewers for their helpful comments. This work was financially supported by the NSF of China (#60772038, #31101609) and research fund for the doctoral program of higher education of China (#20120008120015).

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