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Research Paper

Segmentation of touching insects based on optical flow and NCuts

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Counting the number of rice pests captured via light traps each day is very important for monitoring the population dynamics of rice pests in paddy fields. This paper focuses on developing a segmentation method for separating the touching insects in the rice light-trap insect image from our imaging system to automatically identify and count rice pests by photographing them on a glass table. When placed on the glass, many specimens may be touching, which interferes with automated identification. To segment touching insects, this paper describes a method in which the glass table is lightly tapped between successive images, which causes the specimens to move slightly. Optical flow is computed between the two images captured before and after insect motion. Normalized cuts (NCuts), with the optical flow angle as the weight function, was applied to separate the touching insects according to the number of insects in each connected region. We compare our method with the *k*-means and watershed methods. Our method achieves an average rate of good segmentations of 86.9%. In our future work, we will focus on the identification and counting of rice light-trap pests.

1. Introduction

Monitoring rice pest population dynamics in agriculture by surveying pest species and assessing the density of the pest population in paddy fields is very important for pest forecasting decisions. Ultraviolet light lamps are widely used to trap insects in paddy fields for monitoring rice pests. The trapped insects are brought to the laboratory the next day. Firstly, plant protection technicians visually identify and manually remove the insects which don't damage or heavily damage rice from all trapped insects. Then, they identify and separate the rice main pests according to their species. Finally, they count these main pests separately. We refer to such pests as "light-trap pests". The resulting counts are used to estimate the pest density in the paddy fields. Multi-site and frequent identification and counting of rice light-trap pests is time-consuming and tedious for plant protection technicians, especially near the pest occurrence peak. This can lead to low identification accuracy, low counting accuracy, and long delays in obtaining accurate counts. These problems can in turn lead to poor decisions about rice pest management.

We have developed an insect imaging system to automate rice light-trap pest identification and counting based on machine vision and image processing (Yao et al., 2012). This

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system consists of a glass plate, two digital cameras, four light sources, stainless steel holders to fix camera and light sources, a computer and software (Fig. 1). After the rice light-trap insects are brought back to the lab from the insect light trap in the paddy field, they are sorted via different size mesh screens and then spread on the glass plate. Two cameras capture both top and bottom views of the insects to obtain more pest image features which can then be used for subsequent automatic pest identification. Because the background of each image may contain the other camera, mounting bars, table legs, and so on, the colour-difference method is employed to remove the background (Yao et al., 2012). When the rice light-trap insects are spread on a glass plate, some insects touch or overlap (Fig. 5a). These touching insects need to be digitally separated before insect image feature extraction, species identification and counting. Dozens of different species of insects are trapped by the UV light lamp. They display different poses (with wings spanning or folding, leg bending or straight), different sizes (variation from 2 mm to 25 mm), and different body or wing coloration (variation from black, green, brown, tawny to tattletale grey); this raises big challenges for any image processing method that seeks to separate these touching insects. This work is mainly focussing on developing a segmentation method for middle-sized touching insects in the image from top camera. We are inspired by the optical flow method used to detect moving targets. If we lightly tap the glass plate by hand, the location and orientation of the insects on the glass plate is changed slightly. By capturing an image before and after tapping the glass plate, we can isolate the individual insects by the optical flow computed from the two images. However, the computation of optical flow suffers from ambiguity of correspondence, which is the well-known aperture problem. We apply the normalized cuts (NCuts) algorithm (Shi et al., 1997) to accurately separate the touching insects based on the optical flow angle.

The rest of the paper is organised as follows. Section 2 discusses the segmentation methods for insect images and the application of optical flow and NCuts. Section 3 introduces our method for segmenting touching insects based on optical flow and NCuts. Section 4 presents some examples of segmenting touching insects using our method, k-means and watershed. Section 5 discusses the average segmentation performance results of the three methods. Finally, Section 6 draws some conclusions about the performance of our system, the segmentation method of touching insects, and discusses subsequent rice light-trap pest identification and counting.

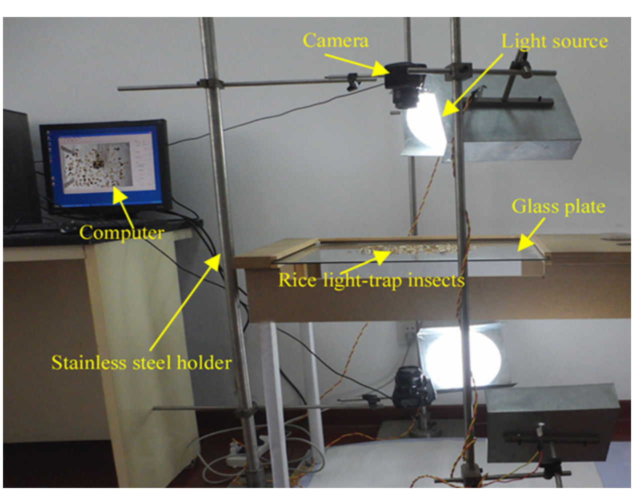

Fig. 1 – Rice light-trap insect imaging system.

2. Related work

We divide our discussion of related work into three parts. First, we review related work on segmentation methods of insect images. Then, we review the application of optical flow and NCuts respectively.

2.1. *Segmentation methods for insect images*

Some segmentation methods have been used on insect images for insect identification and counting (Yao et al., 2011; Wang & Ji, 2011). Studies of insect segmentation mainly focus on three aspects:

(1) Segmentation of individual insects from the background for insect identification and counting has received the most study and application. Threshold methods based on image features were used most in insect image segmentation. Zhang, Hu, and Qiu (2003), Luo et al. (2006) and Yu and Shen (2001) used histogram-based threshold, adaptive threshold and fuzzy set entropy-based threshold methods to segment stored-grain pests and *Lepidopterae* from the background respectively. Some clustering methods have been used in insect image segmentation. Chen, Hu, and Zhang (2007) used k-means clustering algorithm to inspect wheat leaf pests. Zhao, Liu, and Yao (2009) used the rough set and Fuzzy C-means clustering to segment sugarcane cotton aphid area from background for aphid counting. Mou, Zhao, and Zhou (2009) used the improved fuzzy C-means clustering based on simulated annealing algorithm for stored-grain image segmentation. Chen, Geng, Zhou, and Huang (2009) proposed a method of expectation-maximisation (EM) clustering using multi-features to segment insect images.

In addition, other segmentation methods have been used for insect segmentation. Shariff, Aik, Hong, Mansor, and Mispan (2006) used the multi-resolution segmentation method to discriminate pests and non-pest species in the images. Zhao and Chen (2007) proposed GaborBoostSVM method to segment pests from the background by unsupervised classification. Martin, Moisan, Paris, and Nicolas (2008) used adaptive image segmentation method which can tune algorithm parameters with respect to variations in leaf colour and contrast to detect the pests in greenhouses. Zhang and Guo (2010) used the graph cuts to segment stored grain insects.

(2) Segmentation of the insect body and appendages for insect morphology analysis and identification. Huang, Guo, and Zhao (2003), Zhang and Liu (2004) used the mathematical morphology method to segment feet and feelers from the trunk of stored-grain pests. Hao and Ni (2009) used

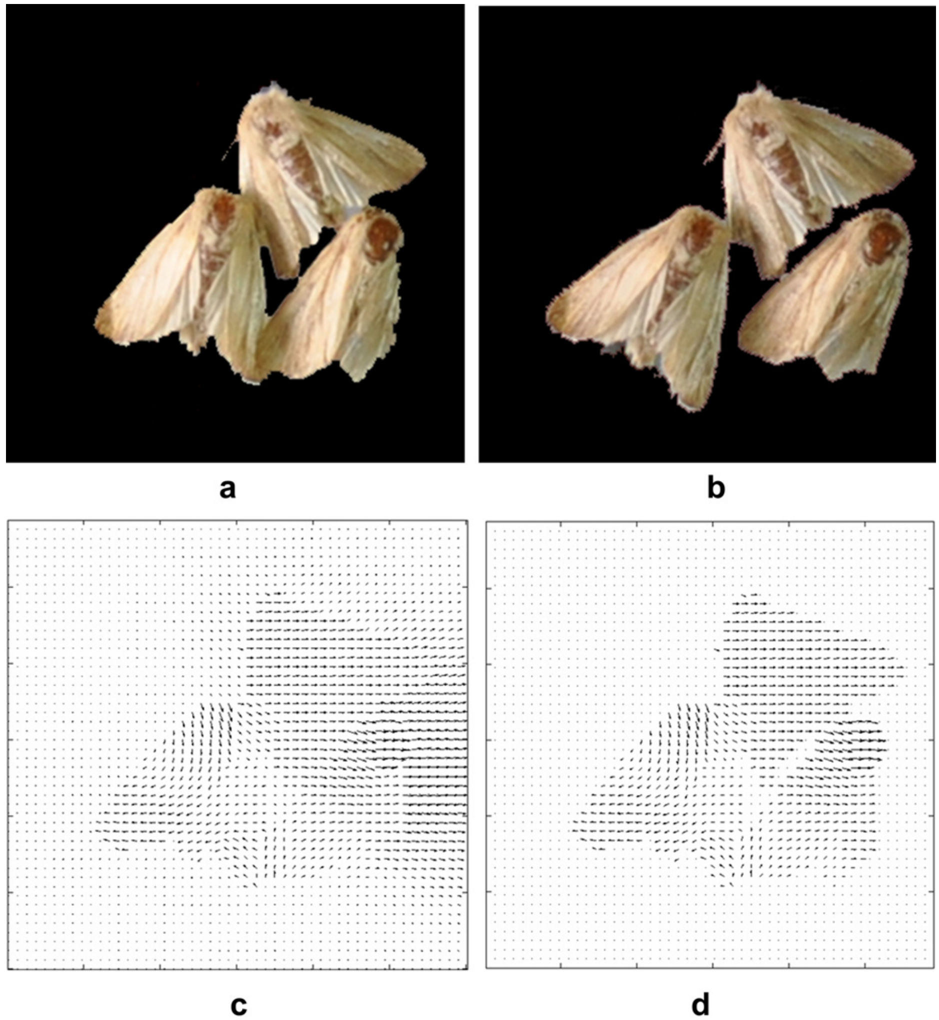

Fig. 2 – Two images before and after lightly tapping the glass plate and optical flow vectors. (a) Image before tapping the glass plate; (b) Image after tapping the glass plate; (c) Optical flow vectors of Fig. 3a and b; (d) Optical flow vectors of insect region in Fig. 3a and b.

adaptive threshold algorithm to segment different parts of *Bactrocera*. Blasco et al. (2009) used a fixed threshold based on the histogram to segment a fly from the background, then analysed the contour of the fly abdomen based on the segmented image and used Fast Fourier Transform features to detect the presence of the ovipositor for determining the sex of the live fly in five high-resolution images of each insect.

(3) Segmentation of touching insects has seldom been studied. Wang and Peng (2007) used a watershed algorithm to separate touching stored-grain pest images based on mathematical morphology for detecting pests. Weng (2008) used the watershed segmentation algorithm based on *a priori* information to restrain the impact of the background and insect wings when counting flying insects. This method is designed for large insects (such as locusts) and not for identification.

In this paper, we discuss the segmentation of touching insects belonging to multiple species for identification and counting of rice light-trap pests. The segmentation results should maintain the integrity of each insect as much as possible in order to permit subsequent identification and counting of each insect species.

2.2. *Application of optical flow*

Optical flow is the pattern of apparent motion of objects in a visual scene. It is computed using the brightness constraint, which assumes brightness constancy of corresponding pixels in consecutive frames in an image. It results in a dense field of displacement vectors that describe the translation of each pixel in a region from one frame to the next (Horn & Schunck, 1981). Discontinuities in the optical flow correspond to objects moving at different relative rates and in different directions. Hence, in images where there are differences in motion among different objects, optical flow can help segment those objects (Horn & Schunck, 1981). Popular techniques for computing optical flow include methods by Black and

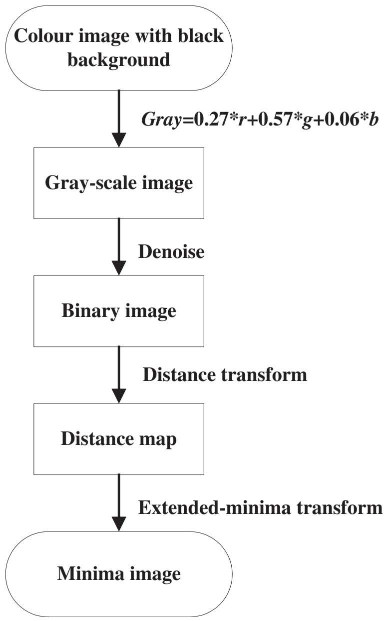

Fig. 3 – The flowchart of determining the number of touching insects.

Anandan (1996), Horn and Schunck (1981), Lucas and Kanade (1981), and Szeliski and Couglan (1997).

At present, optical flow has been applied to many problems, including object detection and tracking (Yilmaz, Javed, & Shah, 2006), object segmentation (Klappstein, Vaudrey, Rabe, Wedel, & Klette, 2009), movement estimation (Redlick, Jenkin, & Harris, 2001), video compression (Mukherjee & Mukherjee, 1999), 3D structure recovery (Zhang & Kambhamettu, 2000) and robot navigation (Ohnishi & Imiya, 2005).

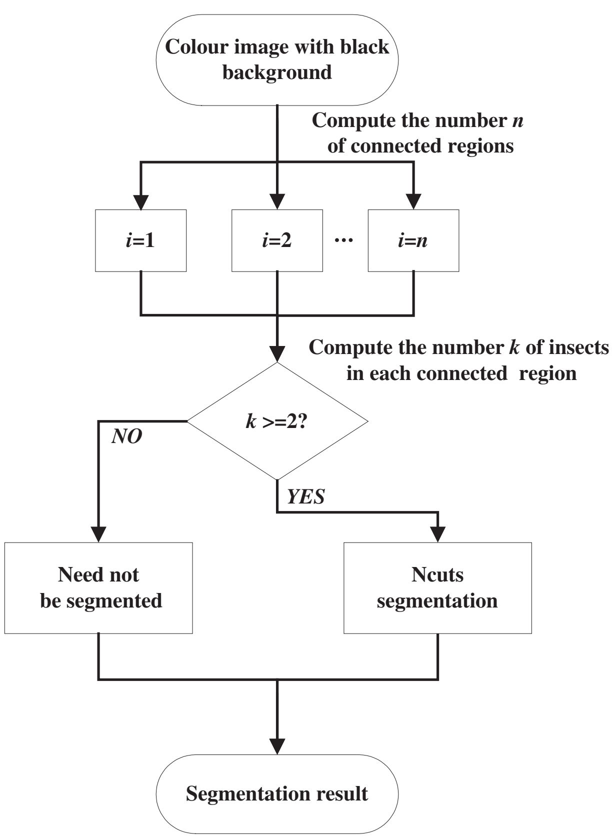

Fig. 4 – The flowchart of segmenting touching insects using NCuts.

2.3. *Application of the normalized cuts (NCuts) method*

The NCuts algorithm was proposed by Shi and Malik (1997) for solving the perceptual grouping problem in vision. NCuts treats image segmentation as a graph partitioning problem using a global criterion that measures both the total dissimilarity between the different groups as well as the total similarity within the groups. NCuts is an unbiased measure of disassociation between subgroups of a group, and it has been widely applied to segment both static images (Zhao, Wang, & Wang, 2007) and motion sequences (Shi & Malik, 1998).

In order to partition an image, NCuts needs a measure of the similarity between every pixel and all other pixels. So the computational complexity becomes greater with increasing image size. To decrease computational complexity, NCuts can be improved by combining it with other methods, such as watersheds (De Bock, De Smet, & Philips, 2004), wavelet transforms (Regentova, Yao, & Latifi, 2006), k-means (Tatiraju & Mehta, 2008) and Nystrom (Belongie, Fowlkes, Chung, & Malik, 2002). These techniques allow NCuts to be applied to regions instead of single pixels.

3. Segmentation method for touching insects

When rice light-trap insects are spread on the glass plate, some insects touch or overlap. These touching insects need to be separated before identifying and counting them. First, we compute the optical flow between two images captured before and after lightly tapping the glass plate by hand to produce insect motion. Then, the location and number of insects in each connected region are determined based on the regional minima method (Gonzalez, Woods, & Eddins, 2003). Finally, the NCuts algorithm is applied to compute an accurate segmentation based on the optical flow angle and the number of insects in each connected region.

3.1. *Optical flow of insect motion*

When we lightly tap the glass plate by hand, the insects on the glass plate move slightly. Two images are captured – one before and one after tapping the glass plate (Fig. 2a,b; only showing three touching insects).

Dense optical flow fields are obtained by computing the flow vector of each pixel under the brightness constancy constraint, $I(x, y, t) - I(x + dx, y + dy, t + dt) = 0$ (Horn & Schunck, 1981). We used the method developed by Sun et al., which is based on the original formulation of Horn and Schunck (Sun, Roth, & Black, 2010). The optical flow (shown in Fig. 2c) is computed from the images in Fig. 2a and b.

In the Horn and Schunck algorithm, the smoothness constraint is necessary in computing the optical flow of objects in motion. However, this assumption is not always correct at

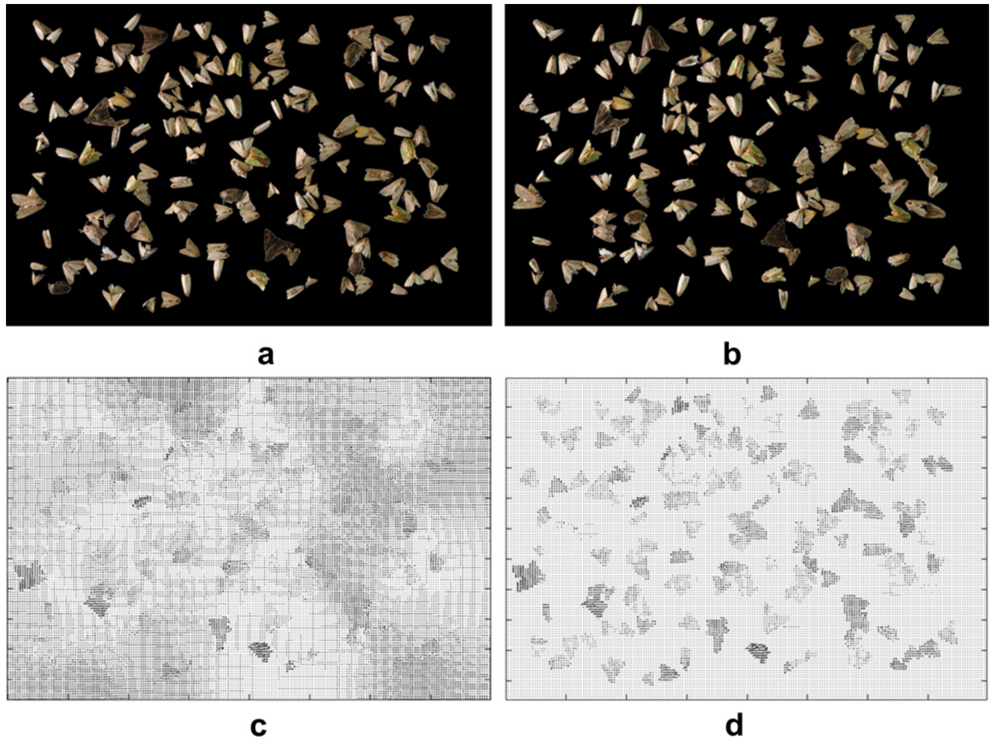

Fig. 5 – Two images before and after tapping the glass plate and optical flow vectors field. (a) Image before tapping the glass plate; (b) Image after tapping the glass plate; (c) Optical flow vector field of Fig. 6a and b; (d) Optical flow vector field of insect regions in Fig. 6a and b.

the boundaries of objects, which results in poor estimation of motion parameters due to the known aperture problem (Marr, 1982): when a straight moving edge is observed through a narrow aperture, only the component of motion perpendicular to the edge can be measured. To reduce segmentation errors caused by inappropriate motion parameterisation, the optical flow of the background is set to zero, and the flow is only computed in the insect-occupied areas (Fig. 2d).

According to the optical flow vectors of insect motion, we find the angles of optical flow provide valuable information for distinguishing different insect individuals. We define the angle θ of the optical flow vector of every pixel in insect region according to the counterclockwise direction in the system of rectangular coordinates in Table 1.

3.2. *Determining the number of touching insects*

In order to apply the NCuts method, we must know the number of desired segments—in this case, the number of touching insects within a single "blob." In our work, we compute the regional minima of an image using 8-connected neighbourhoods to find the location and number of insects in the image captured before tapping the glass plate. The flowchart of the algorithm for determining the number of touching insects is provided in Fig. 3.

3.3. *NCuts based on optical flow angle*

A graph $G = (V, E)$, with V vertices and E edges, can be partitioned into two disjoint subsets A and B, $A \cup B = V$, $A \cap B = \varnothing$. The dissimilarity degree between the two subsets can be computed by total weight of the edges connecting A and B. In graph theoretic language, this is called a *cut*:

$$\mathrm{cut}(A,B) = \sum_{u \in A, v \in B} \omega(u,v) \tag{1}$$

A good partition of a graph is one where the *cut* value between A and B is small. Shi and Malik (1997, 2000) proposed the *normalized cut* (*NCut*) as the minimum cut of a graph

$$\mathrm{Ncut}(A,B) = \frac{\mathrm{cut}(A,B)}{\mathrm{assoc}(A,V)} + \frac{\mathrm{cut}(A,B)}{\mathrm{assoc}(B,V)} \tag{2}$$

where $\mathrm{assoc}(A,V) = \sum_{u \in A, t \in V} \omega(u,t)$ is the total connection weight from nodes in A to all nodes in the graph and assoc(B,V) is defined similarly.

Table 1 – Angle θ definition of the optical flow vector f in the system of rectangular coordinates.

Horizontal ordinate x of f	Vertical coordinate y of f	Angle θ
=0	=0	0
=0	<0	$3^*\pi/2$
=0	>0	$\pi/2$
>0	≥0	$\tan^{-1}(y/x)$
>0	<0	$\tan^{-1}(y/x) + 2^*\pi$
<0		$\tan^{-1}(y/x) + \pi$

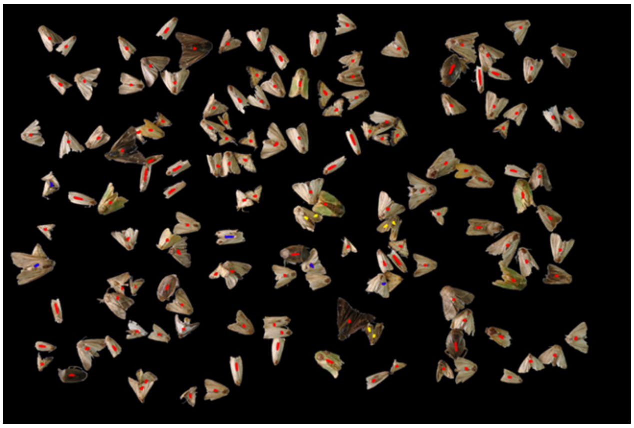

Fig. 6 – Image of rice light-trap insects with 135 individuals. Red points: correct locations of insects. Five blue points: insects that were not found. Six yellow points: one insect is mistaken for two insects.

In our paper, the weight w of two nodes u and v should be as follows:

$$\omega(u,v)=e^{-\frac{|\theta_{fu}-\theta_{fv}|}{\sigma_1}} * \begin{cases} e^{-\frac{|X_u-X_v|^2}{\sigma_2}} & v\in \text{the eight}-\text{neighbor region pixels of } u \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where θ_{fu} is the angle of flow optical vector f of node u, and X_u is the spatial location of node u; σ_1 and σ_2 are constants.

The detailed steps of segmenting touching insects using NCuts are described in Fig. 4.

4. Experiments

We now describe the experiments regarding the segmentation of touching insects using optical flow and NCuts. We first show some images to demonstrate the validity of our methods, and compare them with segmentation results using k-means and watershed. Then we present the results of our experiments using the three methods.

4.1. *Compute optical flow*

The background of two images (Fig. 5(a) and (b)) captured by one camera before and after lightly tapping the glass plate is removed using the method described in our precursor work (Yao et al., 2012). Then, the images are used to compute the optical flow (Fig. 5(c)). To reduce segmentation errors, we set the optical flow of the background to zero and only compute the optical flow of the insect regions (Fig. 5(d)).

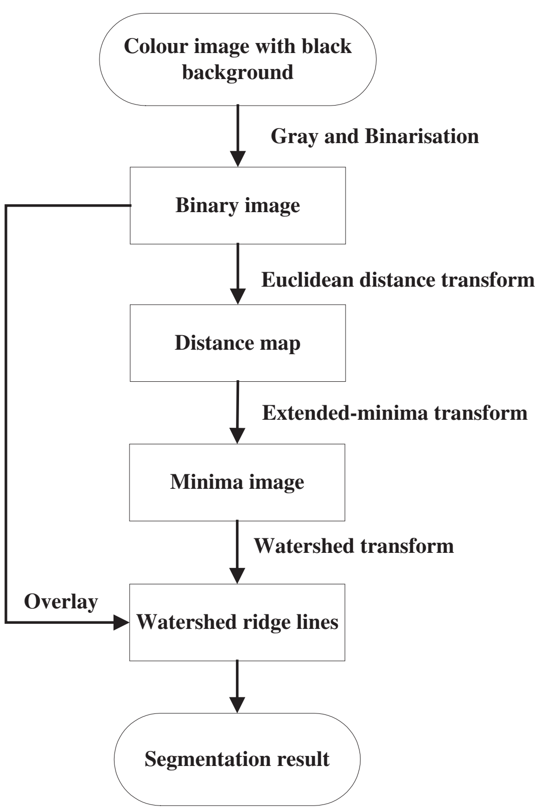

Fig. 7 – The flowchart of the marker-controlled watershed algorithm.

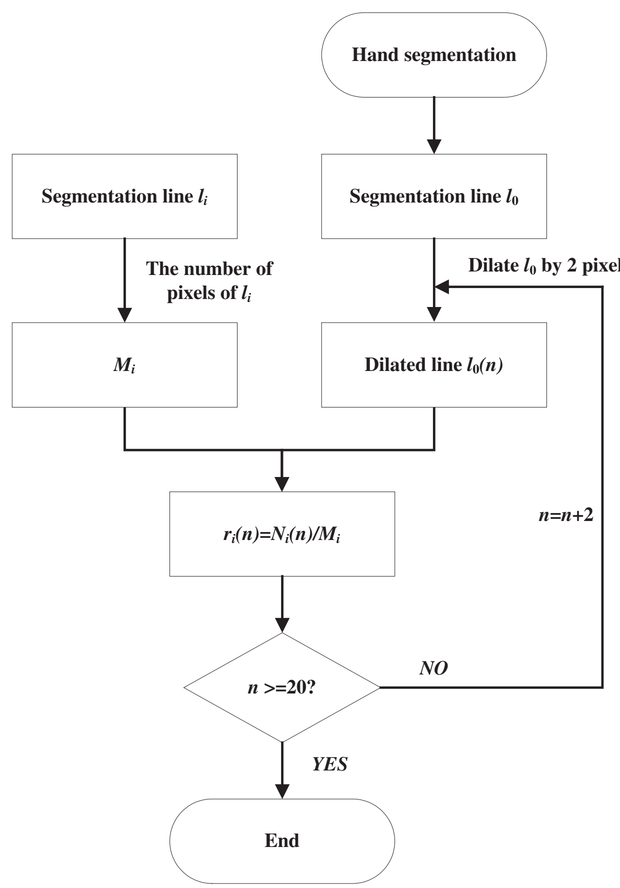

Fig. 8 – The flowchart of the evaluation method for segmentation results.

4.2. *Determine the number of insects in each connected region*

The method described in Section 3.2 is used to determine the location and number of insects in the insect image. We visually inspect the insects in Fig. 5(a) and use different colour marks whether the locations of insects are correctly detected using our method. The correct locations of insects are marked with red points in Fig. 6. Most of the insects are correctly detected and localised. However, a few insects are located wrongly. Touching insects marked with blue points were mistakenly treated as a single insect, and single insects marked with yellow points were mistakenly divided into more than one insect.

4.3. *Competing segmentation methods*

We compared our NCuts approach to the k-means and watershed algorithms. To segment using the k-means algorithm (Lloyd, 1982), we describe each pixel in the original image using three features: the horizontal ordinate x, vertical coordinate y, and the optic flow angle θ (as defined in Section 3.1). We then apply k-means with k set to the estimated number of insects in the blob (from Fig. 6). The hope is that each cluster will correspond to a single insect.

To segment using the watershed algorithm, we use the marker-controlled watershed algorithm (Parvati, Prakasa Rao, & Mariya Das, 2008) to avoid the over-segmentation phenomenon. The flowchart of the marker-controlled watershed algorithm is provided in Fig. 7.

To evaluate the performance of the three segmentation methods, we compute the ratio between the number of pixels making up the computed segmentation boundary line and the number of pixels in dilated versions of the hand segmentation line. We plot this ratio as a function of the amount of dilation. A perfect segmentation would exhibit a ratio of 1 with zero dilation, but this is extremely difficult to achieve. If one method achieves a larger ratio than another for the same amount of dilation, then its segmentation accuracy is better. The flowchart of the evaluation method for segmentation results is provided in Fig. 8.

We can also measure the accuracy of a segmentation by computing the overlap between the true area of each insect segmented by hand and the area of the region

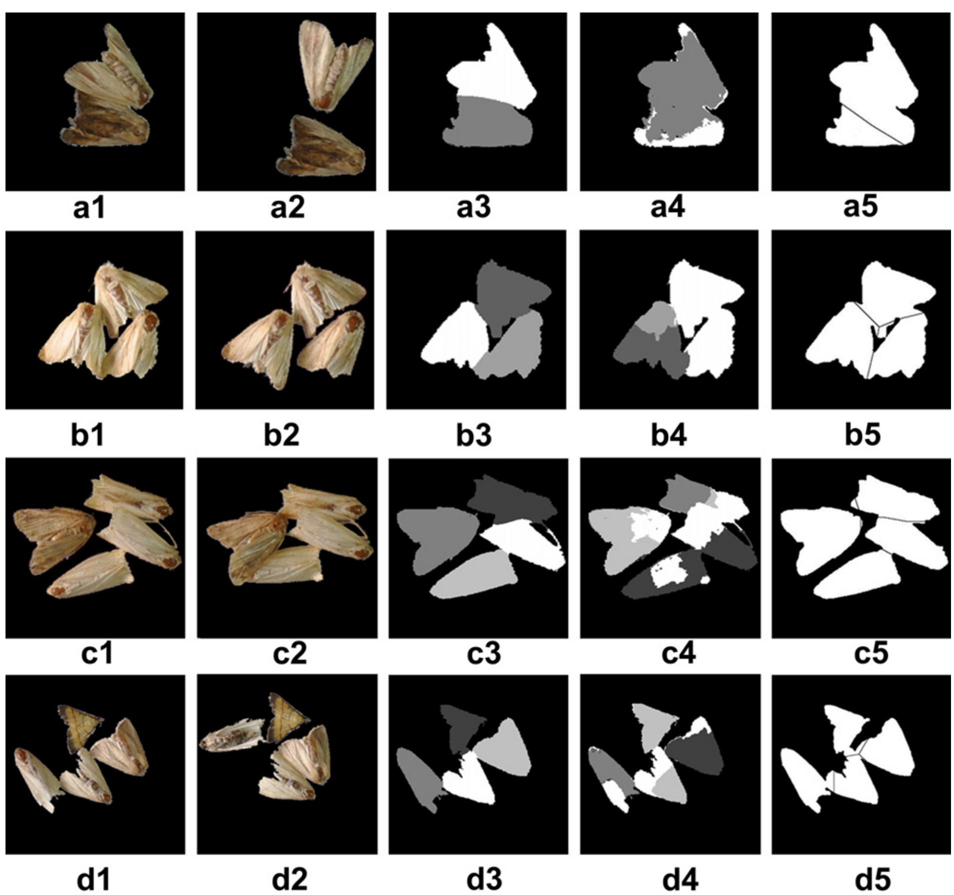

Fig. 9 – The segmentation results using NCuts, *k*-means and watershed. (a1, b1, c1, d1) show the original images of touching insects; (a2, b2, c2, d2) show the images after insect motion caused by lightly tapping the glass plate; (a3, b3, c3, d3) show the segmentation results using NCuts based on the optical flow angle; (a4, b4, c4, d4) show the segmentation results using *k*-means based on three optical flow parameters; (a5, b5, c5, d5) show the segmentation results using the watershed algorithm.

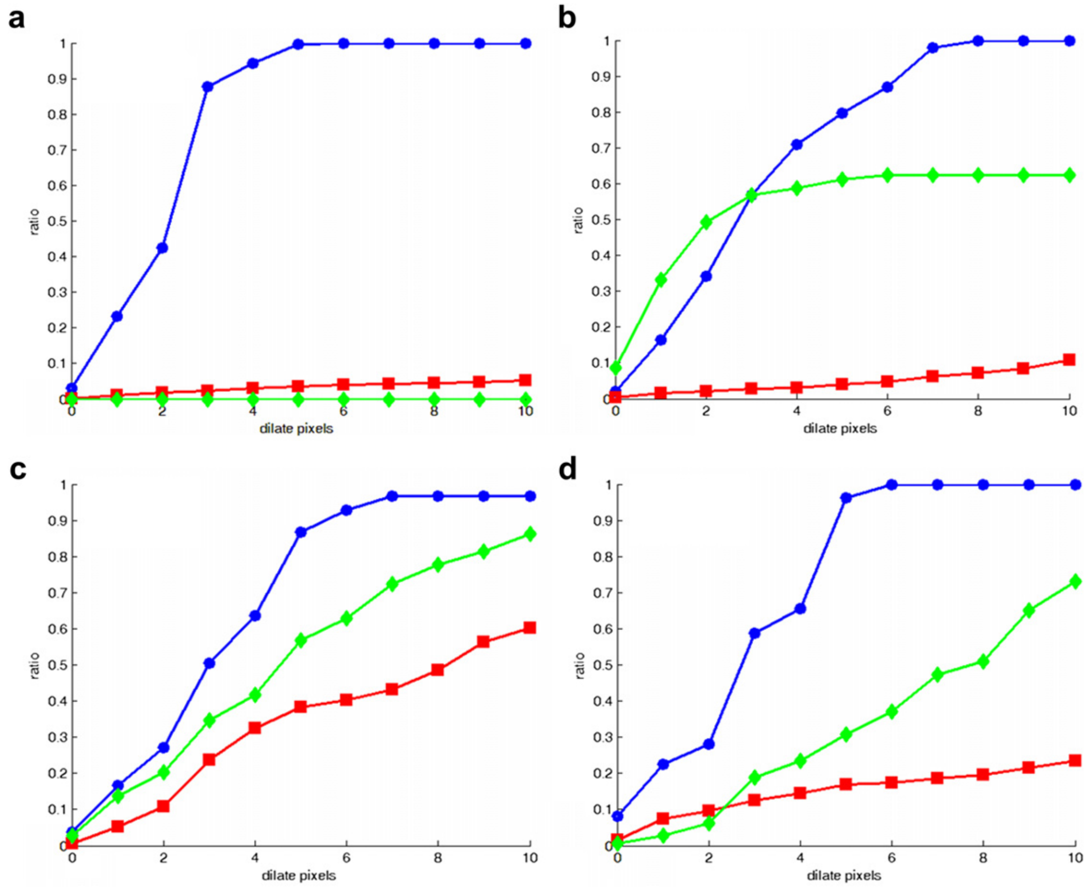

Fig. 10 – Segmentation performance on touching insects using NCuts (blue circles), watershed (green diamonds) and *k*-means (red squares). (a, b, c, d) show the segmentation performance for Fig. 9 (a1, b1, c1, d1) respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

segmented by NCuts segmentation algorithm. If the overlap accounts for at least 70% of the segmented region, we consider it to be a successful segmentation, since in our experience, 70% overlap is enough to support accurate species identification.

4.4. *Segmentation results of four images of touching insects using three methods*

Fig. 9 shows examples of segmentation results by three methods. Fig. 9 (a1, b1, c1, d1) shows four original images of touching insects (image size: 300 × 300 pixels). Fig. 9 (a2, b2, c2, d2) shows the corresponding images after insect motion was induced by lightly tapping the glass plate. Fig. 9 (a3, b3, c3, d3) shows the segmentation results using NCuts based on the optical flow angle and the estimated number of insects in each blob from Fig. 6. Fig. 9 (a4, b4, c4, d4) shows the segmentation results using *k*-means. Finally, Fig. 9 (a5, b5, c5, d5) shows the segmentation results using the watershed algorithm. Fig. 10 (a, b, c, d) shows the performance of three segmentation methods for the images of touching insects from Fig. 9 (a1, b1, c1, d1).

The segmentation results for NCuts are excellent, with 70% overlap in every case. The *k*-means segmentations are

Table 2 – Detection results of the insect number in connected regions.

Insect number in one connected region	Number of correct detection	Number of incorrect detection	Accuracy of detection based on blobs (%)	Accuracy of detection based on insect individual (%)
1	687	6	99.1	92.7
2	105	17	86.1	
3	40	10	80.0	
4	8	3	72.7	
Total	840	36	95.9	

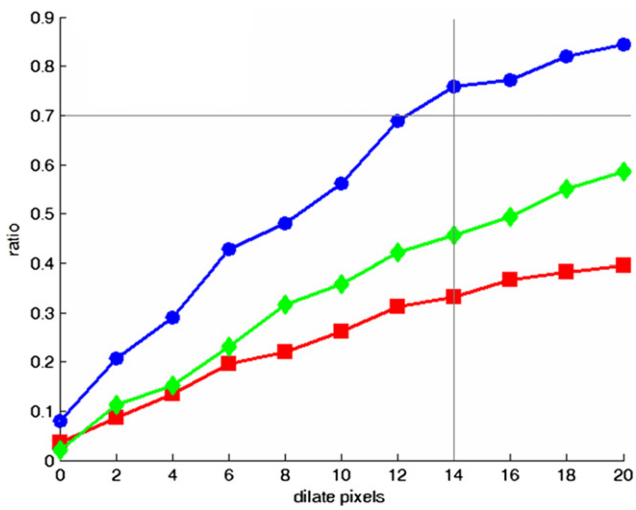

Fig. 11 – Average segmentation performance on touching insects using NCuts (blue circles), watershed (green diamonds) and *k*-means (red squares) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

much worse. It seems that the three features of each pixel do not differ enough between individual insects to permit successful clustering. The segmentation results using the watershed method are slightly better, but some insects are divided into extra parts, and the outlines of insects are significantly changed. The resulting shapes would cause significant problems for species identification using shape features.

From Fig. 10 (a, b, c, d), we see that the pixel ratios rise as the number of dilated pixels increases for the three segmentation methods. However, the ratio for the NCuts segmentation algorithm is obviously higher than the ratios for the *k*-means and watershed algorithms. In Fig. 10(a), the ratios for watershed and *k*-means are close to zero at 20 dilated pixels, which means these two methods perform poorly for segmenting the image in Fig. 9 (a1). In Fig. 10(b), the ratio for watershed is larger than for NCuts when the number of dilated pixels is less than 6, which means the segmentation performance of watershed is better than NCuts. However, the segmentation performance of NCuts segmentation improves as the number of dilated pixels increases. From Fig. 9 (b5), we see that the watershed segmentation changes the outlines of insects. In Fig. 10 (c) and (d), the segmentation performance of NCuts is the best, watershed is inferior to NCuts, and *k*-means is the worst.

5. Results

To evaluate the method for estimating the number and location of each insect, we tested nine images containing 1131 insects. After background subtraction, there are 876 blobs (connected regions of insect pixels) of which 693 contain one insect, 122 contain two, 50 contain three, and 11 contain four touching insects. If touching insects in a blob are mistakenly treated as a single insect and a single insect is mistakenly divided into more than one insect, all insects in this blob are regarded as being wrongly detected. We measure the accuracy of insect detection based on blobs and on individuals. Table 2 shows the results. We attained an accuracy of 95.9% based on blobs and an accuracy of 92.7% based on individual insects. As the number of insects within a blob increases, the accuracy of detecting the individual insects decreases. We found that in some groups of touching insects, one of them would be localised incorrectly or missed entirely. This happened particularly when the insects were heavily overlapping. In other cases, one insect was mistaken for two insects, often as the result of partial occlusion and unusual viewing angles.

To compare the average segmentation performance of the three segmentation methods on touching insects, we tested the 183 “blobs” of touching insects containing two (122 blobs), three (50 blobs), and four (11 blobs) insects. Fig. 11 shows the results. We note that the segmentation performance of NCuts is the best of the three segmentation methods. When the hand segmentation boundary line is dilated by 14 pixels, more than 70% pixels of the NCuts segmentation boundary lines fall within the dilated region.

To further evaluate the NCuts method, we test the 183 “blobs” of touching insects. An insect is correctly segmented if the best segment found by NCuts covers at least 70% of the visible area of the insect. Table 3 shows the results. We see that the overall accuracy of good segmentations is 86.9%, and that it does not depend much on the number of insects in each blob.

To test the efficiency of our method, we compute the segmentation time of one image including 92 blobs of which 61 contain one insect, 13 contain two, 10 contain three, 7 contain four and 1 contains five, based on optical flow and NCuts. We scale the original insect image to the size 900×598 pixels. Our segmentation algorithm is run in Matlab 7.0. The run time totals about 306 s (optical flow: 254 s; NCuts: 52 s). We

Table 3 – Rate of good segmentation of touching insects using NCuts based on optical flow.

True number of insects in a connected region	Number of regions	Number of regions correctly segmented	Ratio of good segmentations (%)	Average ratio of good segmentations (%)
2	122	105	86.1	86.9
3	50	45	90.0	
4	11	9	81.8	

think the time can be shortened through algorithm optimisation or using C language.

6. Conclusion and future work

In this paper, we described the method for segmenting touching insects based on optical flow and NCuts. Optical flow was computed only in insect areas of the two images captured before and after insect motion by lightly tapping the glass plate. A method based on regional minima was applied to locate each insect and obtained an accuracy of 95.9% in determining the number of insects in each connected region. NCuts with the weight function of the optical flow angle was employed to separate the touching insects based on the estimated number of insects in each connected region. The percentage of good segmentations was 86.9%. We compared our method to *k*-means with clustering parameters of optical flow vector and watershed. Our method based on optical flow and NCuts achieved better segmentation results.

There are a few details that must be considered in our system. First, the glass plate needs to be tapped lightly multiple times to separate the touching insects to reduce the difficulty of segmentation and identification. Second, a background image without insects needs to be captured whenever the lighting environment is changed or the cameras are moved. Otherwise, we will not achieve a consistent background. Finally, the size of insects within a single image should be as similar as possible to reduce the risk that a larger insect will hide most or all of a smaller insect.

Some insects are damaged after light-trapping, and some are incomplete because of insect overlap or inaccurate segmentation. It is difficult to identify them. A challenge for future work is to find a set of features of rice light-trap insects that permit accurate species identification. A second challenge is that the light trap collects both pest insects and non-pest insects. The non-pest insects do not need to be identified and counted. So it would be desirable to have a method for rejecting these non-target insects without first identifying their species. This is because training a classifier for species identification requires a large number of training examples, and this may be hard to obtain for less common non-pest species.

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