An Approach to Detecting Brown Plant Hopper Based on Morphological Operations

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Abstract. Detecting brown plant hopper (BPH) population in images is recently concerned to support the insect monitoring application in agriculture. Combination of this research topic and the light trap systems may help to automate the counting of BPHs falling in the traps, which is currently done manually. In this paper, a new approach to detecting BPH in images based on morphological operations will be proposed. By applying these operations appropriately, shape structure and size of the BPH in images can be identified and the number of BPHs can be counted. This allows to detect BPH in images more effective and accurate, and reduce time and effort in doing this task. In addition, we also propose a method for removing noise (inserts other than BPH) in images based on the weight and color factors. The experimental results show that the proposed approach is suited for detecting and counting BPH in images.

Keywords: Brown plant hopper detection · Morphological operations · Image processing

1 Motivation and Related Work

Brown plant hopper (BPH) is one of the most dangerous insect for rice plants. It harms rice plants by directly feeding on them and transmitting many serious diseases such as ragged stunt virus and grassy stunt virus. This leads to serious losses of rice fields. As the result, BHP is causing serious damages on Vietnamese agriculture as well as other rice-growing countries [4,8]. For example, in the Mekong Delta of Vietnam, the BPH outbreak caused the loss of around 1 million tons of rice in 2007, which resulted in a government freeze on the export of rice. The Office of Agricultural Economics in the Ministry of Agriculture and Cooperatives of Thailand reported that the outbreaks caused losses worth $52 million during the dry season of 2010 [4].

Monitoring BPH can help to identify appropriate time for starting crops to reduce the damage of brown plant hopper. Many approaches have been proposed to eliminate the damage of BPH on rice plants. One of them is to create new rice varieties that have the BPH resistance capability. Many rice varieties that are resistant to the brown plant hopper represent their life long history of breeding

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and successful application in the field [7,8]. More than 20 resistance genes to BPH have been identified and they have been used to create rice varieties resistant to BPH such as Mugdo, ASD 7, etc. [7,8]. However, adaptation of BPH to resistance limits the effectiveness of resistant rice varieties. Therefore, it is necessary to find out more approaches to deal with this problem.

Another approach to detecting BPH infestation is based on SPAD reading and reflectance of the rice. The results in [5,14] show that SPAD reading and reflectance from rice are significantly effected by BPH infestation. The spectral reflectance from rice canopy significantly decreased in the near-infrared wavelength range as BPH infestations increased. The ratio indices of SPAD readings are also significantly related to BPH infestations. The main effects of BPH infestations on SPAD reading and reflectance are consistent regardless of nitrogen application rates. Therefore, these factors can be used to detect BPH infestation in rice fields. The results of these research show that this is a potential approach to detecting BPH infestation in rice fields. However, reflection and SPAD values from the leaves are not only effected by BPH infestation but also many other factors such as nitrogen-fertilizer and the kind of leaves.

On the other hand, Prasannakumar N.R. and Chander Subhash proposed a regression pest-weather model to describe the relation between BPH light trap catches and weather parameters [11]. The empirical results show that weather parameters such as maximum/minimum temperature, rainfall, humidity and sunshine hours are closely correlated with BPH light trap catches. Although empirical pest-weather model have significantly contributed in understanding pests population dynamics, it is influenced by local conditions and thus behaves in a location-specific manner. The pest population is thus shown to be affected by different factors at various locations.

Another approach to this problem is to apply the information techniques such as image processing [6,12] and digital signal processor [15]. In these studies, the authors proposed several approaches to detecting BPH in images based on machine learning (e.g. AdaBoots, SVN, etc.) and image processing techniques (e.g. single-threshold segmentation, wavelet transform) to detect BPH. In addition, in [15], the mathematical morphology de-noising operations were also used to remove noises from the images. Basically, these studies can detect BPH in the image automatically. However, they still have limitation: (i) some of them have not been well-investigated [15]; (ii) the preprocessing and de-noising step are still simple and ineffective that leads to the detection accuracy was only about 70 %–85 % [9,12]; (iii) some of them cannot count the BPH in images [6]. In addition, the morphological operations have not been used effectively. They were mainly used for de-noising and removing the redundant details in the images while their capability is beyond this task.

Therefore, in this paper, we propose an approach to counting BPH in images based on morphological operations. These operations are used to identify the morphological characteristics of BPH in images. The result of this task will be combined with the well-studied morphological characteristic of the BPH to detect and count them. In addition, we also use these operations in conjunction with the color and size of the BPH in the preprocessing step to remove noises in the images to increase detection accuracy.

This paper is organized as follows. The proposed approach to detecting and counting BPH in images based in morphological operations is described in Sect. 2. It is followed by the description of our method to removing noises in images in Sect. 2.3. We present the experimental results in Sect. 3 and conclusion in Sect. 4.

2 Detecting BPH Using Morphological Operations

In this section, we will propose a model for BPH detection based on morphological operations which are used to highlight the morphological characteristics of BPH. They are recognized based on the matching between their well-studied morphological characteristics and those are identified by the morphological operations.

2.1 Morphology of Brown Plant Hopper (BPH)

BPHs have yellowish brown body and their head overhangs towards the front. Their wings are transparent and the front wings have a black spot at the back side. The morphological characteristics of the BPH depend upon their stage. The BPH egg has crescent shape (about 0.3 to 0.4 mm) and whitish. In this stage, the BPH is not damage the rice. The BPH nymphs are small, have creamy white with pale brown tinge. Their color gradually turns into light brown when growing. The length of the adult BPHs body differ depending on their type. Adult male BPH body length is about 3.6 mm to 4.0 mm while female BPH body length is longer, about 4.0 mm to 5.0 mm. The whole body of the long-wing BPHs are covered by their wings while only a part of the short-wings BPHs body are covered by their wings. The BPH are most damaged at the nymph and adult stage. In our system, the detection is mainly based on the shape and size of the BPHs. Their color will be used to remove the insects other than BPHs.

2.2 Morphological Operations

Mathematical morphology is a theory and technique for analysing and processing geometrical structures based on set theory, lattice theory, topology, and random functions [13]. It contributes a wide range of operators to image processing that are particularly useful for the analysis of binary images. The common usages of these operators include edge detection, noise removal, image enhancement and segmentation.

Morphological operators often take a binary image and a structuring element as input and combine them using a set operator. They process objects in the input image based on characteristics of their shape, which are encoded in the *structuring element* (also known as *kernel*). The two most basic operators in mathematical morphology are *erosion* and *dilation*. Other morphological operators are defined based on these operators including the *opening* and *closing* operators. In this section, we will introduce these operators applying to binary images only. A binary image I can be considered as a set of *pixel location* in the foreground: $Q_I = \{p|I(p) = 1\}$, in which $p = (u, v)$ is a location in I.

Structuring Element. The structuring element consists of a pattern specified as the coordinates of a number of discrete points relative to some *origins*. For the binary image, a structuring element H is a small image in which each pixel has a value of 0 or 1: $H(i, j) \in 0, 1$. Some basic structuring elements are square, diamond, cross, diagonal cross, horizontal line, vertical line.

Erosion. The erosion of an binary image B by a structuring element S, denoted by $B \ominus S$, is a set of points x such that H is included in B when its origin is placed at x: $B \ominus S = \{x \mid H_x \subseteq B\}$. The basic effect of the operator on a binary image is to erode away the boundaries of regions of foreground pixels (i.e. white pixels, typically). Thus, area of foreground pixels shrink in size, and holes within those areas become larger.

Dilation. The dilation of an binary image B by a structuring element S, denoted by $B \oplus S$, is a set of points x such that H hits B when its origin coincides with x: $B \oplus S = \{x \mid S_x \cap B \neq \emptyset\}$. The basic effect of the operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels (i.e. white pixels, typically). Thus areas of foreground pixels grow in size while holes within those regions become smaller.

Opening. The opening operators of an binary image B by a structuring element S, denoted by $B \circ S$, is defined as the erosion of B by S followed by the dilation by S: $B \circ S = (B \ominus S) \oplus S$. This operator makes stray foreground structures that are smaller than the S structure element will disappear.

Closing. This operator is also derived by the erosion and dilation operators. The closing operator of an binary image B by a structuring element S, denoted by $B \bullet S$, is defined as the dilation followed by the erosion operators: $B \bullet S = (B \oplus S) \ominus S$. This operator preserves background regions that have a similar shape to the structuring element, or that can completely contain the structuring element, while eliminating all other regions of background pixels.

2.3 Brown Plant Hopper Detection Model

In this section, we will propose a model for detecting and counting BPHs in images based on morphological operations and the sequential region labeling algorithm. The model is shown in Fig. 1 which includes three steps: (i) preprocessing, (ii) identifying BPHs in image, and (iii) counting number of BPHs.

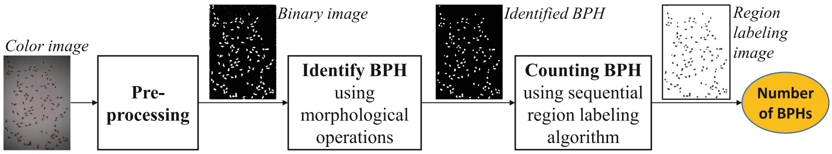

Fig. 1. A model for detecting and counting BPH in images. (Color figure online)

Preprocessing. The objective of this step is to increase the input image quality and convert it into binary image. Images taken by the light trap usually have unbalanced brightness and noise. Therefore, it is necessary to take the preprocessing step to reduce noise and increase quality of the input image to improve the accuracy of the proposed system. In addition, the input image will be converted into binary form so that we can use binary morphological operations in the image to improve performance of the system. This step includes 3 tasks:

1. Convert the input RGB image into gray image using the approach proposed in [3] as follow:

$$I(x,y) = 0.2989 \times R(x,y) + 0.587 \times G(x,y) + 0.114 \times B(x,y) \tag{1}$$

   in which, $R(X,y), G(x,y)$, and $B(x,y)$ are the red, green and blue level of the pixel at (x,y) in the RGB image; $I(x,y)$ is the gray level of the pixel at (x,y) in the output gray image.
2. Increase image contrast using the linear transform histogram algorithm [3]:

$$I'(x,y) = 255 \times \frac{I(x,y) - min}{max - min} \tag{2}$$

   in which, $I'(x,y)$ is the grey level of the pixel at (x,y) in the output image; $I(x,y)$ is the grey level of the pixel at (x,y) in the input image; max and min are the maximum and minimum gray level of the input image respectively.
3. Convert grey image into binary image using adaptive threshold method [1]:

$$B(x,y) = \begin{cases} 1, & \text{if } I'(x,y) > T(x,y) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

   in which, $B(x,y)$ is the binary value of the pixel at (x,y); $I'(x,y)$ is the grey value of the input image at (x,y); $T(x,y)$ is the local threshold value of $I'(x,y)$.

Identifying BPH. The objective of this step is to identify BPHs in image based on their morphological characteristics using the morphological operations. The input image, after preprocessed in the first step, will be applied the morphological two times to highlight the BPHs in the image based on their size.

Firstly, we use the opening operation on the input preprocessed image by the 3×3 diamond structuring element to reduce the small noisy pixel in the image. The structuring element used in this step was selected based on the size morphology of BPH and our experimental result on different type of structuring elements and BPH images.

Next, we apply the opening operation again on the image produced by the above step to remove the objects other than BPHs based on the BPH shape morphology. Several experiments had been conducted to find out an appropriate structuring element for the opening operation in this step. Due to the limitation on the paper's length, detail of the experiments are not presented. Our experimental result suggests the most suited structuring element is the square one. It was produced by combining the different shapes of BPH observed in the images. The opening operation in this step not only helps to remove the object other than BPHs but also helps to separate the remaining BPHs in the image.

Result of this step is demonstrated in Fig. 2.

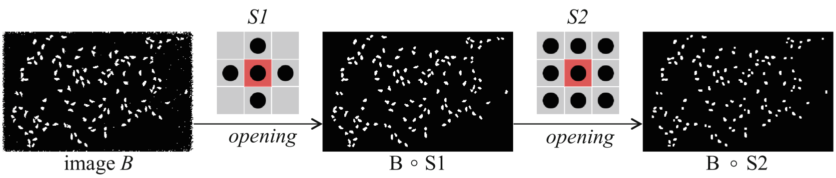

Fig. 2. Identifying BPHs using the opening operation.

Counting BPH. To count BPHs in the processed image, we use the sequential region labeling algorithm with the 4-connected neighborhood. The number of BPHs is the number of labeled areas. Figure 3 demonstrates the result of applying the sequential region labeling algorithm on the image produced by the above steps in Fig. 2.

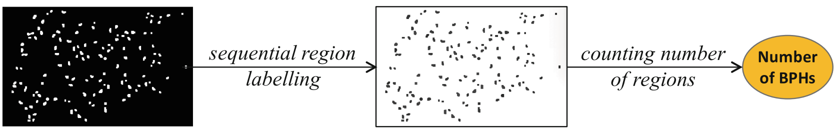

Fig. 3. Counting BPHs based on sequential region labelling algorithm.

Removing Other Insects in Image. Images taken in the field, particularly the light-trap images, usually contains other insects like whorl maggot, zigzag leafhopper, etc. To increase detection accuracy, we also propose an approach to removing insects other than BPH based on the size and color morphology of BPH.

Adult and nymph BPH size is from 3.6 mm to 5 mm. Support that the distance between camera and the base of light trap is 20 cm (a typical distance), size of the BPH in images will be about 9 to 40 pixels. Therefore, to remove the insects other than BPH, we will remove objects whose size is greater than 40 pixels.

Beside the size, we also consider the color of BPHs in removing the insects. The most used color system is the RGB. However, the RGB color system is not suitable for recognizing the BPH color in light trap images as the brightness condition when taking the images may be vary from image to image. Therefore, it is not apparent to identify the real color of BPHs in the image to compare with the color morphology of BPHs (which is the yellow-brown color). In addition, in the RBG system, a color is the combination of red (R), blue (B) and green (G). The yellow-brown color is the combination of non-continuous value of the R, G and B, that will cause difficulty in detecting the BPH color.

In this context, the HLS color system [10] is more suited as the hue value can describe the color of BPHs without the effect of brightness. We can use hue value to identify the range of BPH color in image. By observing the BPH color, we identify the HLS color range of BPH as follow:

$$BPH_{HLS} : \begin{cases} 0 \leq L_{BPH} \leq 0.1 \\ (0 < H_{BPH} \leq 40) \cap (S_{BPH} < 0.3) \cap (0.1 < L_{BPH} \leq 1) \end{cases} \tag{4}$$

in which, L_{BPH}, H_{BPH} and S_{BPH} are the L, H and S value of BPH. The algorithm for converting an RGB value to HLS value can be found in [2]. Based on the size and color morphology of BPHs as analysed above, we propose an algorithm for removing insects other than BPH as in Algorithm 1.

2.4 The Algorithm

Algorithm 2 implements our proposed approach to counting BPHs in image described in Sect. 2.3. This algorithm takes an RGB image as the input and returns a region-labeled image and the number of BPHs in the image.

3 Evaluation

To evaluate the proposed system, we used a dataset that includes 180 images (containing 181,405, BPHs). This dataset had been created by a simulated light trap system in which the BPHs were intentionally drop into a base. For each case, the images had been taken in different conditions (light and noise). The dataset can be divided into 8 groups: (1) balanced light, no other insect, no noise; (2) balanced light, other insect, no noise; (3) balanced light, no other insect, noise; (4) balanced light, other insect, noise; (5) unbalanced light, no other insect, no noise; (6) unbalanced light, other insect, no noise; (7) unbalanced light, no other insect, no noise; and (8) unbalanced light, other insect, noise.

The experimental result is shown in Table 1. The result shows that the average detection accuracy (F1) is about 93.4 % in which the best result was achieved

Algorithm 1. Other Insect Removal Algorithm – OInstRemoval(I)

Input: A region-labeled image I.
Output: A region-labeled image I' with insects removed.

begin
 const MAX_SIZE = 40 /* maximum size of a typical BPH */
 $I' = I$
 foreach *region* $r \in I'$ **do**
  /* calculate the average of R, G and B value in r */
  $R_r = \frac{\sum \text{(R value in r)}}{sizeof(r)}$; $G_r = \frac{\sum \text{(G value in r)}}{sizeof(r)}$; $B_r = \frac{\sum \text{(B value in r)}}{sizeof(r)}$
  /* remove region if it's bigger than usual BPH size */
  if *sizeof(r) > MAX_SIZE* **then**
   remove r from I'
  /* remove region if it isn't a BPH based on color */
  $(H, L, S) = \text{RGBtoHLS}(R_r, G_r, B_r)$ /* convert RGB to HLS [2] */
  if *(H, L, S) does not satisfy Eq. 4* **then**
   remove r from I'
 return I'

Algorithm 2. Morphological-Based BPH Detection Algorithm

Input: An RGB-image I.
Output: A region-labeled image L and the number of BPHs in the image L.

begin
 /* pre-processing step */
 $G = \text{convertToGray}(I)$ /* convert I to gray using Eq. 1 */
 $G‘ = \text{linearTransform}(B)$ /* increase contrast using Eq. 2 */
 $B = \text{toBinary}(G‘)$ /* convert G‘ to binary using Eq. 3 */
 /* identifying BPHs */
 BI = invert of B /* get the invert image of B */
 S1 = diamond structuring element size 3×3
 S2 = square structuring element size 3×3
 $O1 = BI \circ S1$ /* applying opening operation on BI by $S1$ */
 $O2 = O1 \circ S2$ /* applying opening operation on $O1$ by $S2$ */
 /* removing other insets &counting BPHs */
 $L = \text{seqRegionLabeling}(O2)$ /* L: a region-labeled image */
 $LR = \text{OInstRemoval}(L)$ /* remove other insects, c.f. Alg. 1 */
 n = number of regions in LR /* n: number of regions or BPHs */
 return (LR, n)

on group 1 (balanced light, no noise, no other insect) with 95.72 %. The detection accuracy reduce for the images with noise or unbalanced light. The worst case happens on group 8 (unbalanced light, noise, other insects) with the F1 is 90 %.

Table 1. Experimental result of the BPH detection algorithm.

Group	No of BPHs	BPH Detected	TP	FN	FP	Precision(%)	Recall(%)	F1(%)
1	4445	4191	4134	311	59	98.59	93	**95.72**
2	3514	3506	3263	251	243	93.07	92.86	**92.96**
3	4445	4295	4152	293	143	96.67	93.41	**95.01**
4	3514	3575	3264	250	311	91.3	92.89	**92.09**
5	4445	4180	4123	322	59	98.59	92.76	**95.58**
6	3514	3486	3245	269	241	93.09	92.34	**92.71**
7	4445	4395	4116	329	283	93.57	92.6	**93.08**
8	3514	3676	3238	276	438	88.08	92.15	**90.07**

Table 2. Evaluate the Other Insect Removal Algorithm.

Group	BPH Detected	TP	FN	FP	Precision (%)	Recall (%)	F1 (%)
2	3850	3263	251	587	84.75	92.86	**88.62**
4	4004	3264	250	740	81.52	92.89	**86.83**
6	3855	3245	269	610	84.18	92.34	**88.07**
8	4665	3238	276	1427	69.41	92.15	**79.18**

The experimental result also shows that the appearance of other insects effect on the detection accuracy stronger than the light condition (e.g. group 1 (95.72 %)–group 2 (92.96 %) vs. group 1 (95.72 %)–group 5 (95.58 %)). Other insects also effect on detection accuracy stronger than noise (e.g. group 1 (95.72 %)–group 2 (92.96 %) vs. groups 1 (95.72 %)–group 3 (95.01 %)).

We also conducted a further experiment to evaluate the effectiveness of the *Other Insect Removal Algorithm*. We used the images that contains other insects (group 2, 4, 6, 8) in the above dataset for this evaluation. We run the experiment without the removal algorithm and compare with the result in Table 1. The experimental result is shown in Table 2. The result shows that removal of other insect helps to increase detecting accuracy about 4 % in average.

4 Conclusion

In this paper, we proposed a model for detecting BPH in images, particularly the images from light trap systems which are usually effected by different lighting conditions, noise, etc. This model bases on the morphological operations combined with several image processing techniques for preprocessing the images. In addition, we also proposed an algorithm for removing insects other than BPHs to increase detection accuracy. This algorithm bases on size and color morphology of BPH. The experimental results show a promising result with the average detection accuracy (F1) is about 93.4 %, in which the algorithm for removing other insects helped to increase the accuracy more than 4 %.

To improve the proposed system, we suggest to find out an approach to dealing with the images containing overlapped BPHs. In fact, there are some studies that propose light trap systems with the capability to eliminate the overlapped BPHs. However, most of the in-use light trap systems do not have this feature. Therefore, it is worth to propose a solution for dealing this problem. In addition, the current model should be investigated with different parameters (e.g. the structuring elements, the preprocessing techniques, etc.) to gain more understanding in the system to propose further improvement on the model.

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