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Rice Planthoppers in Paddy Fields

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Abstract

The environment of rice plant-hoppers in paddy fields is complex and variable. It is challenging to remove the background from the plant-hopper by general segmentation methods without a strong generalization. Park photographed brown plant-hoppers in paddy fields with a camera and used some image processing methods to count N. lugens on rice plants for the estimation of plant-hopper density. They set the threshold of plant-hopper area in the binary images to determine whether the region contained a plant-hopper. This method hardly removes noise detections similar to the plant-hoppers.

Keywords: Image segmentation; Rice stems; Pest counting; Handheld device; Pest population; Paddy field

Introduction

In addition, Park's method missed some plant-hoppers because different plant-hopper instars on the same cluster of rice may have different sizes and colours. Zou and Ding designed a recognition system of pests using digital signal processor to count the rice plant-hoppers trapped by a lamp on a white cloth. But the method is not able to replace field surveys of rice plant-hoppers. The goal of our research is to provide a rapid and easy system for the automated counting of rice plant-hoppers in paddy fields. To achieve this goal, we developed a system that combines a handheld device for photographing images of rice plant-hoppers on rice stems with a software system for automated counting the plant-hoppers in the images. The size of rice plant-hoppers is small, from 1 to 5 mm, and the paddy field environment is complex. Each image may contain rice, rice plant-hoppers, other insects, water, dead leaves, dirt, weeds, disease spots and water reflection. It is difficult to remove such a complex background using general image segmentation methods [1]. To reduce labour intensity and improve efficiency, a hand-held device was developed for easily collecting images of rice plant-hoppers on rice stems. With this device, the surveyor does not need to stoop down to collect rice plant-hoppers onto an enamel plate by tapping the rice for visual counting. Instead, the surveyor just holds the pole with one hand and places the camera close to the rice stems. The smartphone is held with the other hand. It can connect to the digital camera by WiFi, control the camera by the remote viewfinder application and share a low-resolution version of the image in the camera lens [2]. The surveyor previews the rice image on the smartphone screen and moves the pole until the camera finds a good view. We found that the false detection rates at all grades decreased significantly. The detection rate also decreased slightly, which means that some plant-hoppers are mistaken as non-plant-hopper forms by the second layer of detection. To further reduce the false detection rate, the third layer of detection based on the threshold judgment of three features was applied to the sub-windows as detected by the SVM classifier. The false detection rates at all grades decreased significantly. In ninety-two images, we finally obtained a detection rate and a false detection rate. However, we found the detection rate is the smallest and the false detection rate is the highest in low-density plant-hopper images. It is mainly because the total number of plant-hoppers on one image is small, which results in a low detection rate and a high false detection rate.

Discussion

A few issues must be addressed before our method is ready for field testing. First, the handheld device only captures one side of one cluster of rice. A model should therefore be developed to predict the number of plant-hoppers on one full cluster of rice using our counting results. Second, the classifiers are only trained using images of the white-back plant-hopper S. furcifera [3]. Two other species, N. lugens and L. striatellus, often appear on rice in paddy fields together with S. furcifera and damage rice plants. In practice, the three species of plant-hopper should be counted respectively. So we need to train the classifiers using the three species of plant-hoppers in order to count each kind. Third, the false detection rate is relatively high when the plant-hoppers are young. It is mainly because the young plant-hoppers produce small image areas which provide fewer image features and the classifiers are not able to identify them well. At low plant-hopper densities, our method exhibits a high false detection rate. Further research should focus on the detection of the young plant-hoppers and low plant-hopper densities [4]. Finally, the surveyor can't see the rice stem clearly during the heading stage because the plant grow bigger and closer together, which makes the paddy fields look like a canopy and blocks the surveyor's sight. Under these conditions, the handheld device may touch the rice leaves, or mud. The camera on our handheld device should be equipped with a waterproof cover to avoid contamination. Additionally, in this dark situation, the quality of the images may be affected. Training images from the rice heading stage should be added. Accurate pest counting is very important in agriculture for the estimation of pest population density and dynamics in fields which allows for precision pesticide application. At present, counting pests by human visuals is drudgery. Due to the complex environment background of living pests, it is a big challenge to automatically identify and count them by image processing. Many researchers in fields of pattern recognition, artificial intelligence and machine learning are developing some technologies to automatically identify and count pests, which may make the work easier and the results accurate. Beyond the capturing of images of rice plant-hoppers in paddy fields, the handheld device has many other potential applications for the detection of pests and diseases on crops or other

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plants [5]. The detection method can be used to automatically count small objects in complex and variable environments when combined with other image features. The handheld device can easily capture images containing rice plant-hoppers on rice stems. The surveyor can adjust the length of the pole and move the camera close to the rice stems using the extendable pole. The surveyor can use the mobile phone to control the camera via Wi-Fi to capture plant-hopper images on the rice stems without continuously stooping down and standing up and visually counting the plant-hoppers. These images are saved on an SD card in the camera in real-time, and the automated counting of the plant-hoppers in the rice images is achieved using three layers of detection. The detection methods achieved detection rate and false detection rate. This not only reduced labour intensity and visual fatigue in surveyors, but also improved the counting accuracy of rice plant-hoppers. The purpose of the software system is to automatically count the rice plant-hoppers on the rice stems based on image processing. We developed a detection method using three layers of detection algorithm to detect and count the plant-hoppers in the images [6]. We adopted the AdaBoost classifier as the first layer of detection. The plant-hoppers were detected directly from the complex rice background rather than attempting to first removes the complex background. A high detection rate and a high false detection rate were obtained. To reduce the false detection rate for plant-hoppers, the second layer of detection, which is based on HOG features and a SVM classifier, was employed to further determine whether the sub-windows detected in the first step contain rice plant-hoppers [7]. To remove water drops and water reflections, the third layer of detection was developed. In this step, these factors were removed using a threshold value judgment of three features after an automated removal of the background. The detection results were evaluated by the detection rate and the false detection rate. The detection rate is the ratio of the number of the detected plant-hoppers to the number of all plant-hoppers in an image [8]. The false detection rate is the ratio of the number of the non-plant-hopper sub-windows mistakenly detected as plant-hoppers to the number of all detected sub-windows. According to the morphologies and the locations of plant-hoppers on the rice stems, we selected eleven Haar like features. These features are extracted from the positive and negative examples using an integral image method to reduce the computation time and to train the cascaded classifiers [9]. In our work, four cascaded classifiers were combined into a strong AdaBoost classifier. The AdaBoost classifier is treated as the first layer of detection of plant-hoppers on rice images. In the false detection sub-windows, we find that some impurities, exuviates, water, reflected light and dead leaves on the rice stems are falsely detected as plant-hoppers by the AdaBoost classifier. To reduce the false detection rate, we need a second detector that can reject these false detection sub-windows. We find that some non-plant-hopper forms are still mistaken as plant-hoppers. This is because the HOG features of these forms are similar to those of plant-hoppers. These distracting forms are mostly water drops and water reflections [10]. To further decrease the false detection rate, we extracted three global features of sub-windows that were detected by the second layer of detection after an automated removal of the background using the Muti-Otsu method. We reject these distractions by thresholding the values of these three global features.

Conclusion

Manual rice plant hopper survey methods in paddy fields are time-consuming, fatiguing and tedious. This describes a handheld device for easily capturing plant-hopper images on rice stems and an automatic method for counting rice plant-hoppers based on image processing. The handheld device consists of a digital camera with Wi-Fi, a smartphone and an extrendable pole.

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Conflict of Interest

None

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