An Automated Monitoring System for Controlled Greenhouse Horticulture

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Abstract. In the field of controlled horticulture, various methods have been studied to facilitate the environmental data retrieval. One of the great findings in this research is the attraction of insect's behavior towards the LED lighting of various wavelengths. Previous research shows promising results using LED based insect traps for insect population estimation in greenhouses. Therefore, an automated monitoring system is proposed as a standardization tool for environmental data gathering and estimation of pest population in controlled horticulture settings. The proposed automated monitoring system integrates object recognition models (combination of YOLOv3 and SVM) that identify and classify the pest and beneficial population density. The proposed system provides informative output via a mobile application. As a result, the proposed system functions as an integrated IoT management tool that simplifies the information retrieval process.

Keywords: Decision Support System, Stochastic System, Entomological Analysis, Model Evaluation, Object recognition

1 Introduction

In the field of agricultural production, many methods have been integrated to facilitate the retrieval process of environmental data. The term, "environmental data" in this research includes factors such as humidity, light intensity, temperature, pest, and beneficial population density. For temperature and other parameters that can measured with a relative simple single sensor device, the continuous monitoring is state of the art in modern greenhouse settings. However for the monitoring of pest species and beneficial insect populations, no standardized industrial solutions exist.

Pest control in terms of early recognition of possible infestation and rapid counter measures is an important economical aspect in controlled horticulture, since unrecognized infestation lowers the yield, and unnecessary deployment of chemical pesticides is expensive. Pest control has been defined as a method used to monitor and limit pest populations in an ecosystem [1]. The effective methods for the control of the population of herbivorous insects are divided into three categories, namely, chemical pest control, natural pest control, and biological pest control. The chemical pest control in the agricultural field is wide-spread and consists of application of pesticide treatments in the greenhouse or open field [2]. Studies show that the targeted herbivorous insects in the long run develop resistance towards the pesticides used. Gradually, more harmful pesticides are developed in order to efficiently kill off the herbivorous insects. Research shows that continuous pesticide treatment may lead to distortion of agricultural systems [3]. On the economical side, chemical treatment can be rather cost intensive, especially when applied preventively, without detailed monitoring and analysis of the current pest species and grade of infestation.

On the other hand, natural pest control is the control towards parameters such as fungus, illumination, wind, temperature, wave, and many other environmental parameters to ensure that they are not suitable for pest development. Biological pest control comprises the introduction of predators, parasitoids, and/or pathogens in order to control the population of herbivorous insects in a certain environment [2]. In the context of agriculture, predators are insects that actively feed on another species of insects as source of nutrients whereas parasitoids are insects that reproduce by laying their eggs in the body of host which eventually kill the host. Predators and parasitoids used in biological pest control are termed as beneficial insects.

When is the ideal time to induce pest controlling activities? In order to obtain the answer to it, an evaluation of the controlled environment must be performed. Theoretically, the process of gathering greenhouse environmental data is performed in a timely manner as a prevention towards outbreaks of pest infestation. However practically, horticultural systems are not fully technically automated, so that unlike in technical systems, we do not have a continuous global view of all parameters of the systems. Horticultural systems typically involve many manual tasks and include many more uncertainties in the operations. In the subsequent section, the well-known techniques used in environmental data gathering of general greenhouses are tabulated.

1.1 Data Acquisition by Manual Inspection

In general, manual visual inspection in data acquisition [4] is the most widely used technique in greenhouses. Previous research shows that sampling by vision techniques is tedious due to the frequent miniature size of individual pest subjects. The process comprises the identification of insect species including different life-stages, the counting of each of those and finally the tallying of all counts. The identification process of top and bottom of a single leaf is as shown in Figure 1. The counts are then recorded accordingly. These data are tabulated for the entire growing season and used as reference for the subsequent seasons as well as for extrapolation of the development of the pest population during the season.

Fig. 1. Manual checking on top and bottom of the leaves.

1.2 Semi-automated Detection with Sticky Trap

For manual visual inspection of the pest infestation, yellow sticky traps are widely used. Also semi-automated approaches have been developed, that combine a sticky trap with a camera observing the sticky trap. Several works or products exist in that area. However, there exist drawbacks. The glue of traps will start dripping if the trap is exposed to the temperatures in the greenhouse for a longer time of automated detection. Moreover, the trap might be covered with too many insects, making automated analysis of the photos impossible. In both cases manual interception still is necessary regularly.

The detection of small biological objects such as insects with approximate dimensions of 2mm is a real challenge, especially when considering large commercial greenhouses which are larger than $85\,\mathrm{m}^2$ of area. Hence, it is not possible to perform a continuous daily control and examine every leaf in the greenhouse. Conventionally, visual observations are formed on a weekly basis with colored sticky traps by human experts. Since this technique does not allow to precisely study the epidemic spatial model, observations on natural support, namely, the manual vision method are favored. Thereafter, the method of adapted sampling significantly contributes to reduce the amount of data and speed up the analysis process.

In 2018, a semi-automated detection system using the Raspberry Pi with a sticky trap is proposed [5]. The detection has been done automatically using the Raspberry Pi Camera Module v2 with Sony IMX219 8-megapixel sensor, which can be used to take high-definition video, as well as still photographs. Specifically, the model implemented consists of the object detection method based on You Only Look Once (YOLO) [6] and the classification method based on Support Vector Machines (SVM) [7]. The mean classification accuracy is 90.18% and the mean counting accuracy is 92.50% on Raspberry Pi [5]. It is still semi-automated as the usability of sticky trap is required to be manually changed in a regular interval. Hence, the semi-automated detection system with sticky trap is available commercially.

1.3 Automated Pheromone-based Trap

Similarly, the automated pheromone-based detection system is designed to attract specific gender of insect species with their pheromone [8]. The developed detection system is done with RetinaNet which combines two feature extraction algorithms ResNet and FPN for classification and bounding box regression. The research shows a mean object recognition precision of 74.6% with mean run time of 23.44s. Nowadays, there are many companies targeting on improvising this setup and sell them commercially. Therefore, getting the correct tool for data acquisition is important in the field of horticulture.

2 Proposed Automated Monitoring System

From the drawbacks of existing semi-automated data collection frameworks, we propose an approach circumventing the drawbacks of sticky traps in automated pest monitoring systems.

2.1 Research Background

The research in [9] demonstrates that *T. Vaporariorum* is highly attracted to green LED light. The attraction of *T. Vaporariorum* to monochromatic green light is caused by a wavelength specific behaviour [10]. Like in other herbivores, such as aphids, this behaviour should be based on two different photoreceptors which are sensitive to blue and green light. A competitive interaction between both, called opponent mechanism enables the insects to discriminate targets according to the reflection pattern in the blue, green, and yellow range, independent from the reflection intensity [11]. This mechanism explains the aphids's unexpected preference towards yellow compared to green. The visible spectrum of yellow is approximately 580 nm of wavelength and contains higher reflection intensity compared to green and lower reflection in the blue wavelength range. Experiment shows that *T. Vaporariorum* favors the narrow bandwidth green LED as the green sensitive photoreceptor is stimulated.

2.2 System Design

The setup of the proposed monitoring system consists of two independent components interacting via an intermediately server. The connections made in and out of the server are recommended to be established through HTTPS Internet Protocol as all appropriate security features are provided. An individual monitoring device consists of two components, namely, the I/O devices and a Raspberry Pi.

The main components of the I/O device are the LED that lights up from the base of the box as the attraction towards insects and a camera that is used to gather surrounding data.

Other subsidiary components such as photoresistor (light-dependent resistor, LDR) and push button are used in order to facilitate the overall usability of the automated monitoring system. In particular, the photoresistor is used as the detection media of surrounding light condition. Once the surrounding light condition is known, the Raspberry Pi sends the required signal in order to make some adjustments toward the brightness condition of the LED base. In addition, the push button is configured in such a way that the Wi-Fi Protected Setup (WPS) is established for each individual monitoring device. Therefore in each use case of the proposed monitoring system, one or more monitoring devices are connected to a single user.

The items used for I/O device in our implementation consists of Raspberry Pi 4 Model B with 4GB RAM, UEye 1007XS-C camera, Sunfounder photoresistor, and a push button.

2.3 Mobile Application

For acceptance of the automated monitoring system it has to be user-friendly. It should be easily installed and maintained and used by the greenhouse staff. In the user point of view, the developed mobile application is able to execute monitoring tasks as follows:

- The configuration of each individual monitoring device.
- The observation of monitoring data and some simple analysis.
- The flexibility of changing the colour of LEDs.
- The setting of threshold limit that user could obtain notification alert.

The primary task of the whole system is to monitor the overview condition of greenhouse environment. Figure 2 shows the mobile interface on setting up the device. In Figure 2, the editing and renaming of individual monitoring device is shown on the left most, while the result of the renaming process is shown in the middle of the figure. In order to facilitate the process of monitoring several devices, the application is able to dynamically add devices with either scanning of QR code on individual monitoring device or entering its device id.

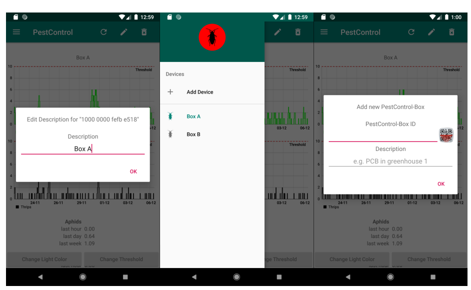

Fig. 2. Mobile interfaces shown during setting up devices.

Figure 3 shows the configurations available and result of data tabulation on the mobile interface developed. The left most interface in Figure 3 illustrates on the selection of light spectrum that is emitted on the LEDs of monitoring device. The LEDs spectrum is crucial in attraction of desired insect species as mentioned in the earlier section. Hence, the user is able to adjust the light spectrum in attracting the appropriate insects for the desired outcome. The middle interface on Figure 3 shows the setting of threshold limit per frame basis on each insect species. These thresholds are subsequently reflected on the tabulated graph. Furthermore, the notification on receiving threshold alert of insect population density is one of the configurations shown. Once the desired thresholds are determined, alert notification will be received when surrounding insect population density reached or surpassed its thresholds. The right most interface shown in Figure 3 indicates the result tabulation in graphical form and a simple analysis of the data collected.

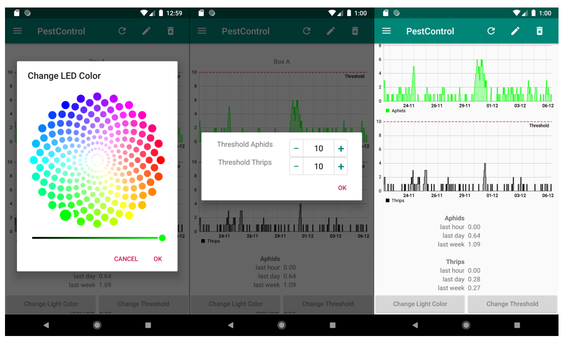

Fig. 3. Mobile interface of I/O density threshold and LED wavelength.

2.4 Software Framework

According to our literature, the software framework that achieves the highest accuracy up-to-date of 90.18% is proposed by Zhong et al. and is adopted [5]. The detection and classification models are pre-trained on a local machine. Once the image is obtained from the I/O device, the Raspberry Pi executes the YOLOv3 detection algorithm on the acquired image. Next, the extracted features are used in the SVM classification algorithm. In this software model, the pre-trained models used are crucial in analysis of result. The implementation of this framework model is suitable as execution of models loaded in the computing device, Raspberry Pi is relatively fast. Hence, it is suitable for our purpose of real-time computing.

3 Result and Analysis

The developed prototype is shown in Figure 4. The details of each I/O device are as described in Section 2.2. Figure 4 shows the overview of implemented prototype on different perspectives and various lighting conditions. This monitoring device is considered as one element of the entire proposed system. On the bottom left of Figure 4 shows the I/O implanted on the Raspberry Pi, namely, photoresistor that is used in brightness adjustment. Subsequently, a WPS push button is installed on the right of the photoresistor for the simplification of user's WiFi configuration.

Fig. 4. Implemented prototype of individual monitoring device.

3.1 Object Recognition Results

Two experimental trials of 14 days each are executed with the implemented prototypes. In each trial, two cages of dimensions (35cm x 70cm x 35cm) are treated with pest population of *Aphis Gossypii* and *Frankliniella Occidentalis* respectively. The sample labelled images data gathered on two insect species for training phase are as shown in Fig. 5.

The training result for YOLOv3 detection model developed is as shown in Figure 6. The loss functions on both training and validation indicate that only small differences between both loss values is found after approximately ten epochs of iterations. Hence, the training is performed sufficiently to prevent huge training loss.

The result of SVM classification with 10-fold cross-validation from the training phase is tabulated in Table 1. The F1-score shows that sufficient training has been performed for the SVM classification.

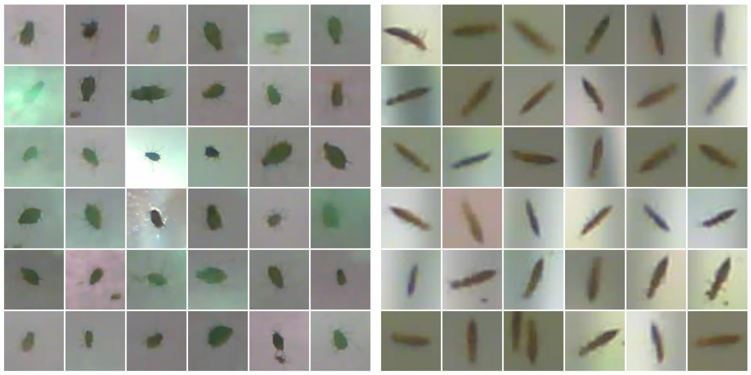

Fig. 5. Labelled data on *Aphis Gossypii* (left) and *Frankliniella Occidentalis* (right).

Fig. 6. Loss Function of YOLOv3 Training.

Table 1. Result of SVM 10-fold Cross-Validation

Class	**Precision**	**Recall**	**F1-score**	**Support**
A. Gossypii	0.99	1.00	1.00	481
F. Occidentalis	1.00	1.00	1.00	481
accuracy			1.00	962
macro avg	1.00	1.00	1.00	962
weighted avg	1.00	1.00	1.00	962

Figure 7 shows the detection process of both pest species with bounding box on each individual object, using the YOLOv3 model developed. Our preliminary study shows that the execution of object recognition including both detection and classification achieves mean accuracy of 83.91% on both classes of pest species.

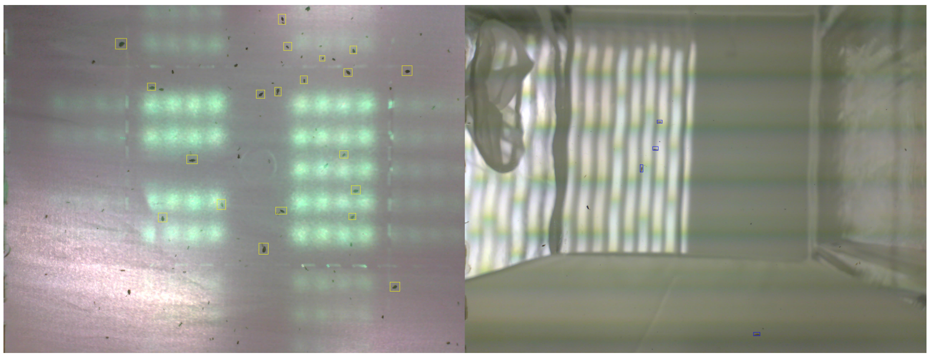

Fig. 7. Detection of individual pest object on images.

4 Conclusions

In our work we present a fully automated insect monitoring system. It is proposed and implemented for the controlled horticulture environment based on secure "wireless network" topology that enables various environmental data to be transferred in real-time. One of the main advantages of a fully automated monitoring system compared to previous semi-automated trap approaches is, that semi-automated traps require regular maintenance as traps have to be changed on a regular basis. Contrary to that, our approach, using adjustable LED illuminated surfaces to attract and count samples of the insect populations in the greenhouse, enables the automated trap to work correctly and without maintenance for a long time (optimally one full growing season), while in other approaches, dripping glue and filled sticky traps still necessitate manual intervention of the greenhouse staff. The IoT enhancement developed in the proposed system is one of possible solutions for reducing the coloured sticky traps and pheromone traps waste produced in the activity of monitoring population density. The proposed automated monitoring system aims to reduce the tedious work on data acquisition of population density. In this paper, possibility of controlling the setup of the monitoring device using an Android-based application is presented. The result is generated in a readable manner and tabulated in a graphical form for the users. In the current prototype, the notifications are set on individual thresholds per frame basis. Thereby, the individual threshold could be calibrated into certain duration basis in the future.

The concept of using single Raspberry Pi as a computing unit for object recognition processes is proven to be sufficient. Furthermore, the Raspberry Pi provides flexibility of integrating various I/O devices as tools to gather the environmental data required, namely light intensity, air humidity, air temperature, and soil temperature. Our preliminary results concerning object detection and classification success is relatively lower compared to other results in the literature. This might partly be caused by variable lighting conditions including uneven background brightness due to the use of LEDs, and also by the relatively small size of our target insects.

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Comments to the reviewers:

We thank the reviewers for their remarks. Especially we tried to correct and/or improve each of the text passages directly indicated by the reviewers one and two. We added AI related literature. For the remarks of all three reviewers concerning the image recognition evaluation and validation:

The aim of our paper is to provide a whole working setting for application in the real world, including usable hardware with low maintenance requirements. We did not strive to improve existing object recognition approaches, but to just use them as found in literature. We found our deployed recognition approach working well enough for our application. The reviewers are right to be interested in a deeper validation of the image recognition approach, however that will only be possible, after we deploy and evaluate the system not only as a prototype but as a working tool in the greenhouse in the next growing season.

The paper has been shortened a bit by rearranging figures and leaving out one or two of minor value to understandability of the paper to meet the conference page limit.