CHEMICAL ENGINEERING TRANSACTIONS
VOL. 58, 2017

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Remigio Berruto, Pietro Catania, Mariangela Vallone

ISBN 978-88-95608-52-5; **ISSN** 2283-9216

DOI: 10.3303/CET1758101

An IoT-based Wireless Imaging and Sensor Node System for Remote Greenhouse Pest Monitoring

Dan Jeric Arcega Rustia, Ta-Te Lin*

National Taiwan University, No. 1, Sec. 4, Roosevelt Rd., Taipei 10617, Taiwan (R.O.C.)
m456@ntu.edu.tw

This study focuses on designing an Internet of Things (IoT) based remote greenhouse pest monitoring system using wireless imaging and sensor nodes (WiSN). The system designed can continuously monitor the number of pest insects detected on yellow sticky papers distributed in multiple locations and can measure the environmental parameters simultaneously. The pest insects are counted through image processing and machine learning algorithms in which it can be classified into black and white objects specifically white flies and fruit flies with an average accuracy of 98% and computation time of 8-9 seconds per image. Data collection was done at a greenhouse in National Taiwan University Experimental Farm in which cabbages were grown as main crop. The greenhouse, without using pesticides, is occasionally infested by white flies and fruit flies. Furthermore, the data are processed by the server in which the real time analysis and monitoring are shown in a monitoring website that also includes the latest acquired yellow sticky paper images as well as the data plots. The feasibility of the system was tested, and the experimental results show that light intensity has the highest correlation with the pest insect count. The developed system is effective to acquire pest count accurately and automatically which provides important spatial-temporal information that allows for efficient integrated pest management in greenhouse operations.

1. Introduction

Insect pests in an agricultural field or facility can cause damage to the crops by infecting the crops with diseases and thus may affect its quality. Nowadays, farmers put insect traps like sticky papers that comes in different colors such as yellow and blue to monitor the number of pests. Different insects are specifically attracted to the colors of the sticky paper commonly such as yellow or blue (Barbedo, 2014; Espinoza et al., 2016). Using sticky papers as monitoring tool, farmers can estimate the density of pests trying to damage the crops. But for very small insects, the counting is very tedious and time-consuming and may be inaccurate at times (Espinoza et al., 2016; Miranda et al., 2014).

The process of counting pests is simplified using image processing. The key point in detecting the number of pests is the process of converting the raw image into the correct color space and equalizing the image according to the current time of day. Barbedo (2014) presented an insect pest detection algorithm for whiteflies by color segmentation using the CMYK color space. The whiteflies are identified from soybean leaves with an accuracy of 95%. On the other hand, Espinoza et al. (2016) devised an algorithm that makes use of the Lab color space and is supported by artificial neural networks (ANN) with 96% accuracy for whiteflies. However, obtaining the images automatically leads to a problem in readjusting the image according to external factors such as glares and foreign objects. Usually, whiteflies are 0.3-0.6 mm in size depending on maturity while an average fruit fly is 3 mm in size. For whiteflies, glares due to sunlight can immediately cause errors to the counting algorithm. To eliminate this problem, adaptive color segmentation is highly suggested for real time application (Xia et al., 2014).

Counting the pests for a relatively large greenhouse and taking individual images of the sticky papers through a camera will take a lot of time and effort (Miranda et al., 2014). As a solution, the use of multiple wireless imaging nodes can be considered in order to make the image acquisition easier. By using the concept of Internet-of-Things, multiple sensor nodes can be deployed in order to not only count the number of insects but also to know the specific area with higher concentration of pests. Accompanied by data processing

Please cite this article as: Rustia D.J.A., Lin T.T., 2017, An iot-based wireless imaging and sensor node system for remote greenhouse pest monitoring, Chemical Engineering Transactions, 58, 601-606 DOI: 10.3303/CET1758101

techniques, the system can provide real time updates for the farm owners and provide alarms or data interpretations for early warning and pest management.
The objective of this project is to monitor the number of pest insects captured in yellow sticky papers and at the same time measuring environmental conditions seamlessly and wirelessly. By the use of an adaptive color segmentation algorithm, an approximate count of the number of black or white insects can be determined. The developed system will allow an efficient integrated pest management for greenhouse operations.

2. Methodology

2.1 System structure and mechanism

Each WiSN is composed of a Raspberry Pi 3, Raspberry Pi camera, and a multi-environmental sensor module. The Raspberry Pi 3 is a system on chip module board that runs with a 1.2 GHz 64-bit quad-core ARMv8 CPU and includes WiFi and Bluetooth communication functions. The Raspberry Pi camera is a visible light camera with an 8 megapixel native resolution image sensor and is capable of 3280x2464 pixel static image acquisition (Raspberry Pi Foundation). The multi-environmental sensor includes a humidity sensor, temperature sensor, atmospheric pressure sensor, and light intensity sensor. The experimental set-up including the wireless node is shown in Figure 1.

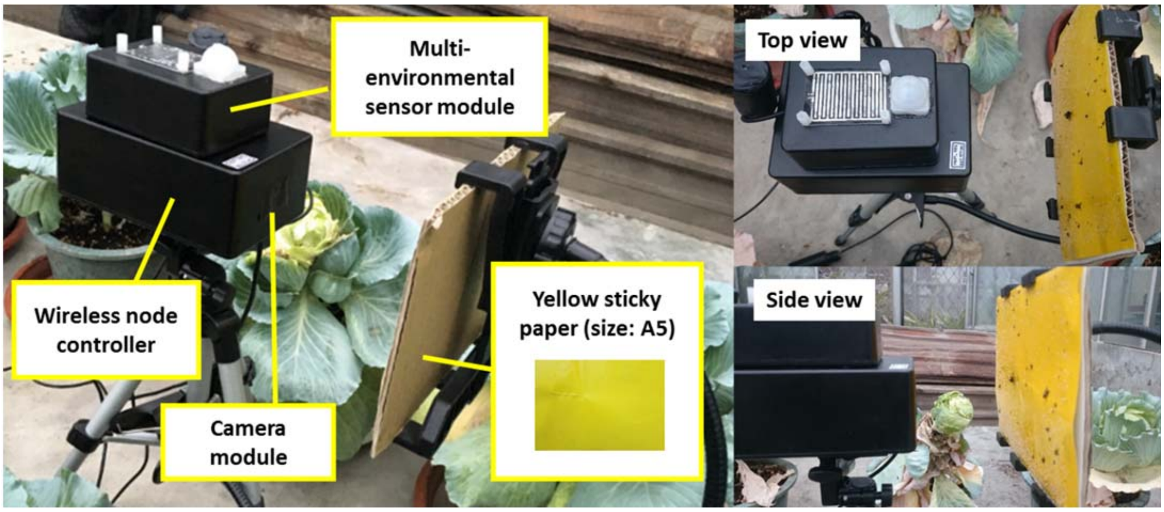

Figure 1: Wireless imaging and sensor node (top view and side view) with part labels

For each greenhouse, in case WiFi connection is not available, there is a 4G router that allows remote internet connection to the sensor nodes using a star WSN topology. Through the internet, the collected images and environmental conditions are sent remotely. Each image obtained from the camera of nodes are taken 8 cm away from the paper. The camera module is set to take images with 3280x2464 resolution with daylight white balancing for automatic image color correction. The images are taken from 7:00AM to 6:00PM on each day every 10 minutes while the environmental conditions are sent every 5 minutes each entire day. In this work, the set-up included two nodes distributed evenly inside the greenhouse.
The server handles the image processing, data processing, and acts as the main web server. An image receiving program is running in the server to process the images and to obtain the corresponding insect pest count. All the data are stored inside a MySQL database and are processed using PHP. Each greenhouse and its nodes are uniquely registered to the server with corresponding IDs. The monitoring website features a real-time update monitoring of the insect pest count and environmental conditions, data plots, and in-depth analysis such as correlation between the insect pest count and the individual environmental conditions. The different greenhouse locations can be selected in order to view its individual nodal data as well as its database number in which can indicate the specific monitoring period. The simplified over-all system structure of the insect pest monitoring system and website sample pages specifically the home and pest monitoring page are shown in Figure 2 and 3, respectively.

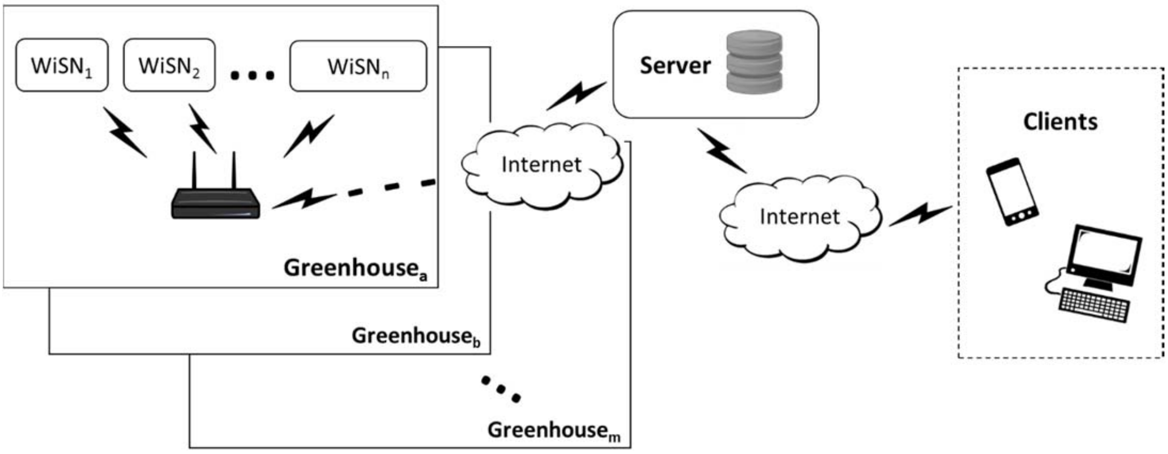

Figure 2: Insect pest monitoring system over-all system structure

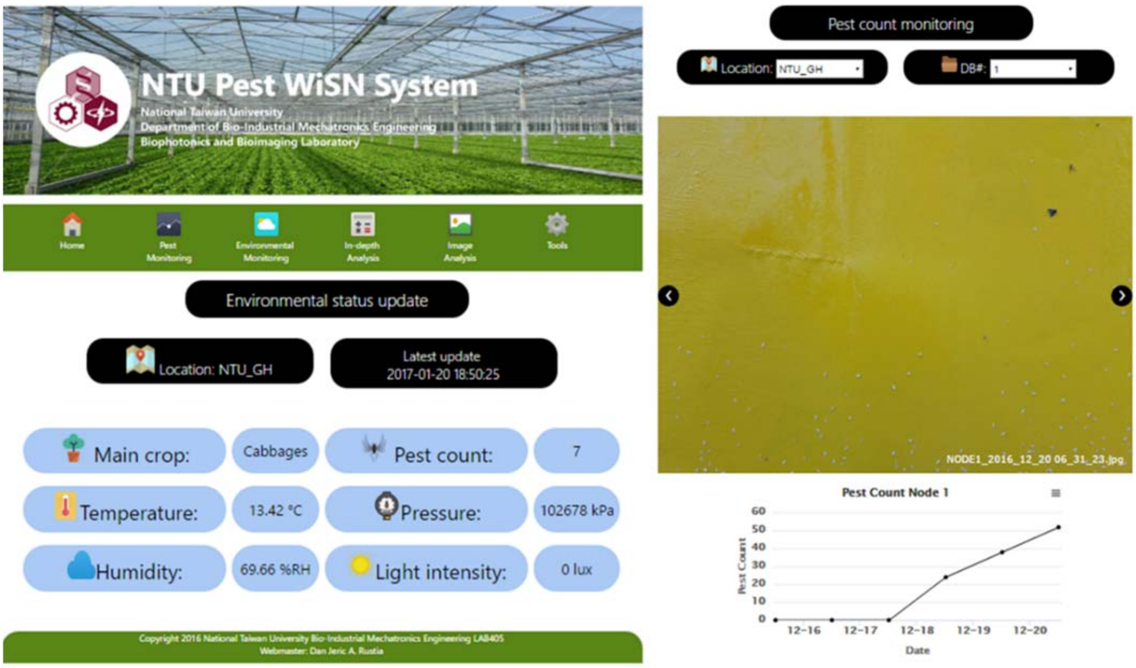

Figure 3: Monitoring website home and pest monitoring sample page

2.2 Image processing

The images obtained are pre-processed by splitting the image into four equally divided regions. The images are equalized using histogram-based contrast and brightness adjustment using reference histograms of images obtained from previous testing results. Each image is converted into CMYK color space using two different threshold value sets for black and white, then undergoes k-means color clustering for color separation classifying into black and white insects. Erosion and dilation morphological operations are applied to the thresholded images and blob counting is done using pre-defined blob radius, area, and convexity. The insect pest count obtained is filtered and processed according to the previous image references from the same hour. This approach detects glares and inaccuracies with the counting results and its specific region. During any of the aforementioned instances, the algorithm is repeated with the adjusted contrast and brightness to reduce the error in counting. Each process takes up to 8-9 seconds computation time without considering the adaptive brightness and contrast adjustment process. A descriptive illustration of the image processing algorithm is shown in Figure 4.

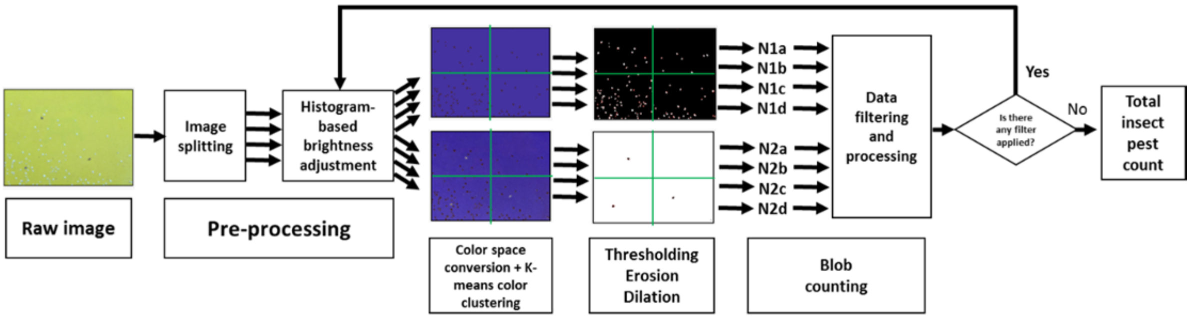

Figure 4: Insect pest counting image and data processing algorithm flowchart

3. Results and discussion

The system was tested during two periods, 12/15/2016 to 12/20/2016 and 1/14/2017 to 1/20/2017. The accuracy of the image processing algorithm was measured by comparing the actual and the experimental insect pest count. The actual insect pest counting was done manually. The experimental results show that the algorithm was able to successfully count the number of insect pests with an average accuracy of 95-98% regardless of the insect pest population as shown in Table 1. Furthermore, the statistical analysis for the two periods are also shown in Table 2 and Table 3 respectively.

Table 1: Summary of image processing algorithm accuracy testing

	12/15/2016-12/20/2016		1/14/2017-1/20/2017	
	Node 1	Node 2	Node 1	Node 2
Total insect pest count	135	222	8	19
Accuracy (%)	98.5	99.0	93.3	97.7
Over-all accuracy (%)	98.7		95.5	

Table 2: Statistical analysis of the environmental parameters (12/15/2016-12/20/2016)

Parameter	Parameter mean		Range		Correlation with insect pest count		
	Node 1	Node 2	Node 1	Node 2	Node 1	Node 2	Mean
Temperature (°C)	19.9	20.6	20.5-23.9	21.49-24.4	0.73	0.84	0.78
Pressure (kPa)	102.218	102.140	101.634-101.871	101.554-101.727	-0.88	-0.99	-0.93
Humidity (%RH)	66.8	68.4	56.4-92.0	84.9-92.2	0.64	0.49	0.56
Light intensity (lux)	1544	1346	0-1522	0-1340	0.75	0.92	0.83

Table 3: Statistical analysis of the environmental parameters (1/14/2017-1/20/2017)

Parameter	Parameter mean		Range		Correlation with insect pest count		
	Node 1	Node 2	Node 1	Node 2	Node 1	Node 2	Mean
Temperature (°C)	17.8	18.8	13.3-18.4	14.4-19.2	0.09	0.68	0.38
Pressure (kPa)	102.146	102.087	102.072-102.678	102.002-102.581	0.27	0.01	0.14
Humidity (%RH)	80.2	81.0	67.9-93.8	77.7-93.5	-0.16	-0.48	-0.32
Light intensity (lux)	1264	1329	0-1322	0-1410	0.18	0.44	0.31

From the observation periods as shown in Table 1, the number of insect pests counted during the second period was significantly less than the insect pest count obtained during the first period. Also, node 2 had relatively more insect pest counts that node 1. From these results, the system proved that it can have an estimate of the concentration of the insect pests in the greenhouse. Furthermore, it was also observed that there is a significant difference between the average temperature and humidity between the two periods while light intensity and pressure are almost similar as shown in Table 2 and 3. Among the two periods, their real-time change in temperature and humidity can also be noticed as shown in Figure 5.

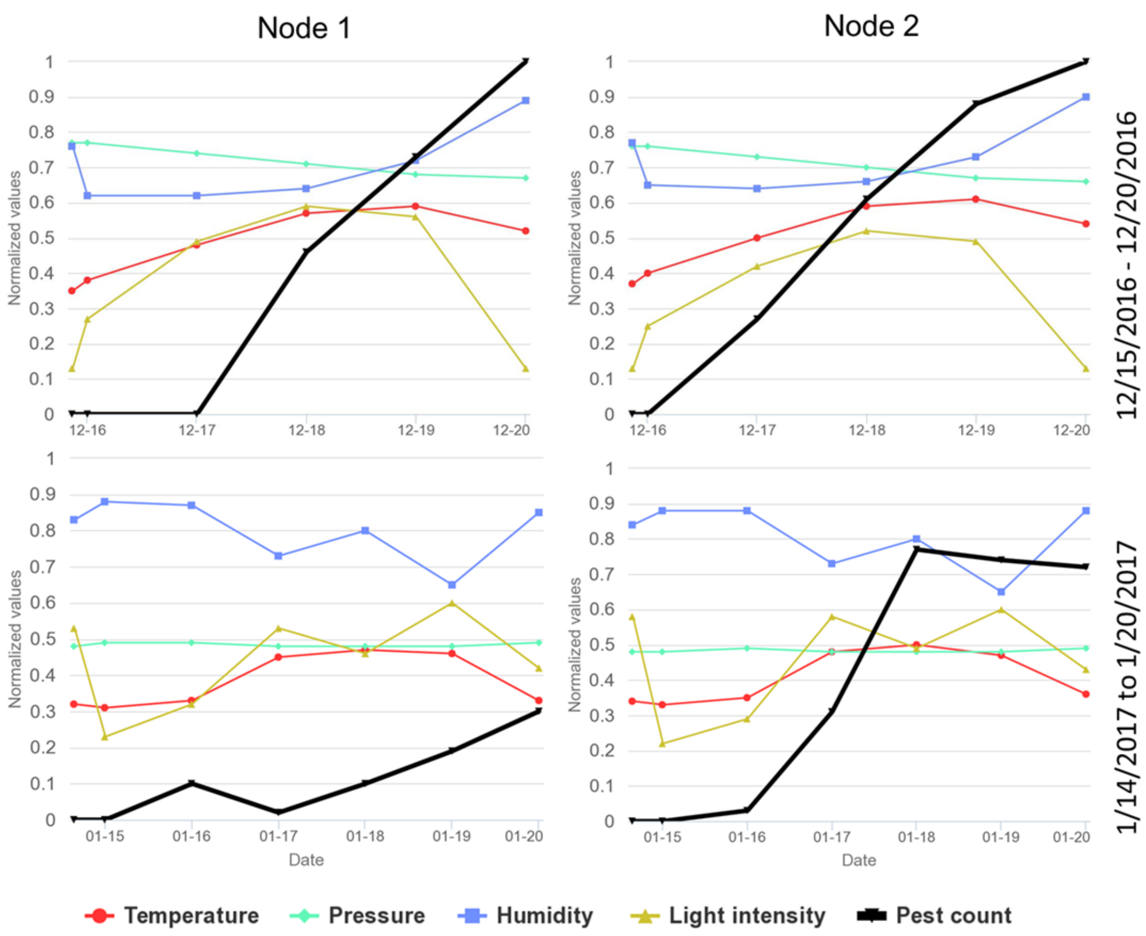

Figure 5. Environmental parameter and insect pest count normalized data plot

In the first period, an observable change in humidity, temperature and light intensity can be seen during the middle of the experiment. This phenomenon led to an abrupt rise in the number of insect pest counts as proven also by their correlation values as shown in Table 2. With a similar case, temperature and light intensity had an increase around 1/16 and 1/17 which caused an increase in insect pest count in node 2. These observations prove that the system can reveal possible relationships between the insect pest count and the environmental parameters. Due to this, further observations between their relationships will be conducted as well as also a plan to consider to make the observation period longer compared to the previous experiments to get a deeper explanation of the phenomena observed.

4. Conclusions

A system capable of monitoring both insect pest count and specific environmental parameters was successfully implemented in this work. The system was able to prove and provide information on the possible causes of infestation of insect pests in crops and know the concentration of the insects in a greenhouse. The findings in this work can be used as reference for future applications such as early insect pest prevention and prediction not only for greenhouse applications but also for field applications. It is recommended that more nodes should be deployed on different locations in order to further prove the capability of the system.

Acknowledgments

The authors would also like to thank the support of Prof. Ju-Chun Hsu of Department of Entomology, National Taiwan University, and her students for assistance and discussions of experiments. This work was supported by a grant (Grant No. 106AS-18.2.1-ST-a1) from the Council of Agriculture, ROC.

Reference

Barbedo, J. G. A., 2014, Using digital image processing for detecting whiteflies in soybean leaves. Journal of Asia-Pacific Entomology, 17, 685-694.

Cho, J., Choi, J., Ji, C-W., Kim, H-Y., Uhm, K-B., Chon, T-S., 2007, Automatic identification of whiteflies, aphids, and thrips in greenhouse based on image analysis. International Journal of Mathematics and Computers in Simulation, 1, 46-53.

Espinoza, K., Valera, D. L., Torres, J. A., Lopez, A., Molina-Aiz, F. D., 2016., Combination of image processing and artificial neural networks as a novel approach of the identification of Bernisia tabaci and Frankliniella occidentalis on sticky traps in greenhouse agriculture, Computer and Electronics in Agriculture, 127, 495-505.

Martin, V., Moisan, S., 2014, Early pest detection in greenhouses

Miranda, J. L., Gerardo, B. D., Tangulig III, B. T., 2014, Pest detection and extraction using image processing techniques, International Journal of Computer and Communication Engineering, 3, 189-192.

Mundada, R. G. & Gohokar, D. V. V., 2013, Detection and classification of pests in greenhouse using image processing, Journal of Electronics and Communication Engineering, 5, 57-63.

Padmanayana, S. M., 2015, Early detection and classification of pests using image processing, International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, 3.

Paek, J., Hicks, J., Coe, S., Govindan, R, 2014, Image-Based Environmental Monitoring Sensor Application Using an Embedded Wireless Sensor Network, Sensors, Basel, Switzerland, 14, 15981-16002.

Park, J., Jones, V. & Hull, L. Automatic monitoring of insect populations, <http://www.cs.cmu.edu > accessed 2.3.2017

Raspberry Pi Foundation, Camera Module – Raspberry Pi <https://www.raspberrypi.org> accessed 2.3.2017

Raspberry Pi Foundation, Raspberry Pi 3 - Model B <https://www.raspberrypi.org> accessed 2.3.2017

Xia, C., Chon, T.-S., Ren, Z. & Lee, J.-M., 2015, Automatic identification and counting of small size pests in greenhouse conditions with low computational cost, Ecological Informatics, 29, Part 2, 139-146.