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Towards Continuous Surveillance of Fruit Flies Using Sensor Networks and Machine Vision

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Abstract— In Australia, the Queensland fruit fly (B. tryoni), is the most destructive insect pest of horticulture, attacking nearly all fruit and vegetable crops. This project has researched and prototyped a system for monitoring fruit flies so that authorities can be alerted when a fly enters a crop in a more efficient manner than is currently used. This paper presents the idea of a sensor platform design as well as the fruit fly detection and recognition algorithm by using machine vision techniques. The experiments showed that the designed trap and sensor platform can capture quality fly images and the invasive flies can be detected with an average precision of 80%.

Keywords: fruit fly monitoring; machine vision; sensor networks

I. INTRODUCTION

Different fruit fly species cause damage to fruit and other plant crops around the world and they are major pests of agriculture. In Australia, the Queensland fruit fly (B. tryoni), is the most destructive insect pest of horticulture, attacking nearly all fruit and vegetable crops. Queensland fruit fly is distributed widely over eastern Australia, including most of Queensland, New South Wales and parts of Victoria, with outbreaks in South Australia [1]. With the global warming effect, more areas will be affected as fruit flies extend from tropical and subtropical regions into temperate regions [2].

In the area covering parts of the states of New South Wales, Victoria and South Australia, B. tryoni populations are actively monitored and if detected treatments are applied so as to drive those populations to extinction [3]. The purpose of the “fruit fly free zone” is to allow fruit produces within that region to have international access for their crops without having to apply costly post-harvest fruit fly disinfestation treatments. Pest “area free zones” are an internationally recognized tool for enhancing trade in fresh commodities, but by international law such zones require constant surveillance to prove that they are free of the pest in question [4].

The national cost for the surveillance and control of Queensland fruit fly in Australia is estimated to be AU$28.5 million/year ($25.7–49.9 million) [2]. If a B. tryoni is detected in the fruit fly free zone, produce export is halted immediately, devastating exports. Currently surveillance is carried out using traps containing a fruit fly specific male attractant which are deployed throughout the area free zone and buffer districts. These traps lure and kill specific species of fruit flies which are then manually collected and identified. The traps’ contents are checked manually on a weekly basis during the fruit fly season and then fortnightly during the winter months. Many man-hours are used to monitor these traps and it still can be over a week before an infestation is detected. Deploying a sensor network to compensate manual checking of these traps gives many benefits. An image sensor can constantly monitor the environment for fruit flies and give real-time alerts of their presence and also removes the need to examine traps that are usually empty.

This paper presents the idea of a sensor platform design as well as the fruit fly detection and recognition algorithm using machine vision techniques. This paper is organized as follows. The next section presents the related work. Section 3 describes the sensor platform design. The detection and recognition of fruit fly is discussed in section 4. Section 5 briefly gives the experimental results and section 6 concludes our work.
II. RELATED WORK

Fruit fly traps of various designs are used to monitor Queensland fruit fly. All current trap designs use a chemical lure to attract male fruit flies to the trap. For fruit flies of interest to Australia, Asia and Pacific, two lures, Cuelure and Methyl Eugenol, are used in traps [5]. Different fly species respond to only one of two lures; B. tryoni for instance is a Cuelure responsive species. Similarly, there are many traps that have been used with varying success to trap fruit flies. Traps such as the Steiner and Tephri-trap have proven successful in trapping different fruit fly species in Australia and elsewhere [6].

Manual insect monitoring is time consuming and laborious. Machine vision technology provides an alternative way to do this. Insects are firstly detected and then recognized using different features. Applications have tended to focus on pest insect recognition such as wasps and leafhoppers [7]. A PDA surveying system has been developed, but this still relies on user input and interactions [8]. We believe a sensor-based automatic insect tracking system can help growers to make management decisions. Such systems will also be useful to officials who certify crops for exports.

III. SENSOR PLATFORM DESIGN

A. Fruit Fly Trap Design

One consideration that has to be made revolves around the lighting conditions and the backdrop inside the trap when capturing images. The clear and yellow plastics used in the Tephri trap provide sufficient light, but the clear plastics make image recognition difficult. Tephri traps kill captured insects via a pesticide that is mixed into the cue-lure and used to attract the flies. An issue is that the flies can move around until their death. Images taken during this time can be blurry and interfere with the quality of the collected data, especially if there is significant movement during this poisoning process. An automated system can also become confused with movement and orientation changes of a fly during this time, deciding there are multiple flies instead of one.

Taking advantage of ideas and technologies from other trap types can aid in this issue. Jackson traps use a sticky substance (Tanglefoot®) on a white surface that makes it easy to notice a trapped fly. But such a trap is not ideal for baiting a fruit fly, let alone taking a picture of it. Therefore applying these ideas to a Tephri trap gives us a new, reliable trap (Fig. 1) with a more controlled environment.

B. Sensor System Design

One of the goals of sensor networks in fruit fly monitoring is to collect data and store them for timely, evidence-based decision making. Like all other sensor networks, the system should be able to combine sensing, computing and wireless communication capabilities. Unlike other mote-based sensors, smartphone sensors have relatively large memory, higher processing power, and can communicate with existing mobile networks directly. Relying on existing mobile networks means that we can better use existing networking facilities and avoid the in-network processing in mote-based systems. Although smartphone sensors need more power, this problem has been solved by using solar panels and large batteries for power supply.

Figure 1. Trap currently used to catch B. Tryoni.

A client-server architecture is employed where a traditional web server is used as the server and mobiles phones as clients (Fig. 2). Mobile phones will monitor the environment, collect data, partially process the data and send them to the server over the network for storage and further processing. Each sensor operates autonomously and follows a recording schedule which is verified each time it contacts the server. Rescheduling can be achieved by updating this schedule through a web-based interface. In the event that a sensor cannot contact the server, it follows the current schedule and the recordings are stored in the phone’s memory card. Once this becomes full, data capture is paused until older files are uploaded and new space obtained.

The web server is the core of the framework. On the backend, it is used by the sensors to upload their data and to download the schedule for recording. On the frontend (the web interface), it is used by users to manage the sensor network, access data online and analyse the collected data. A web-based interface allows users to view images, to tag or annotate them manually and to perform data analysis tasks such as insect identification.

The server manages data and conduct data analysis. Data analysis will first detect whether there are anything in the trap. Once an invasive pest has been found, relevant authorities need to be contacted as soon as possible about this so an appropriate action can take place. Since data is stored both on the server end and on the sensor itself, both of these devices can be used to forward on this warning. The sensors are currently set to send an SMS to a target phone when a suspicious object is detected.
This sensor platform uses Smartphones incorporating 3G/HSDPA and Wi-Fi communication. All the sensors run Windows Mobile operating system and use the .NET Compact Framework. Currently HTC TyTNIIs with three-megapixel CMOS image sensors are being used. Solar panels are used to power the devices.

To sum up, this system comprises two parts: a centralized web server running in the lab and an autonomous sensor program running on individual devices in the field. Users will access this system using web browsers.

IV. FRUIT FLY DETECTION AND RECOGNITION

A. Real-time Detection of Invasive Flies

As the lure is specially designed to capture fruit flies, once an invasive object is detected, it is assumed to be a fruit fly. The fruit fly could be detected by calculating the difference between the template image and the captured image using equation 1. If the difference is larger than the threshold, a message is sent to the expert together with the fruit fly image.

\[
A = \sum(|I_{\text{capture}} - I_{\text{template}}|)
\]

B. Fruit Fly Recognition

The proposed algorithm for recognizing the Queensland fruit fly (B. tryoni) includes the following steps.

1) Image pre-processing: Due to the lower quality lenses that are used in mobile devices, the captured images will occasionally be blurred. Thus, before image segmentation, brightness and color of images are automatically adjusted to the optimum level. We use the histogram equalization as the pre-processing method to highlight the fruit flies. As shown in Fig. 3, after auto-adjusting, the contrast between the object and background is enlarged to make further processing easier.

![Original and auto-adjusted images](image)

Figure 3. Original and auto-adjusted images.

2) Image segmentation: In order to extract the fruit fly from the background, a Level Set image segmentation method is employed [9]. Firstly, the contours are represented as the zero level set of an implicit level set function, and then this function is evolved based on a partial differential equation to fit the edge of the object.

![Segmentation results](image)

Figure 4. Segmentation results.

From the result shown in Fig. 4(b), the boundary of the fruit fly is successfully extracted compared with the manual segmentation in Fig. 4(a), though the contrast between the wings and background is not prominent.

3) Color space transformation: The Queensland fruit fly has distinguished features which make them different from other flies or insects of similar shape and size. This species has three yellow patterns which are located in the middle, top left and top right of the insect’s thorax (Fig. 5(a)). The top left and top right yellow color patterns are approximately symmetric, and middle yellow pattern is always below the top left and right patterns. These color patterns and their spatial relations are utilized to recognize the fruit fly order.

The image is firstly transformed from the RGB color space to the Lab color space because it has better ability in distinguishing the yellow patterns.

4) Fruit fly recognition: The pictorial structure model is employed for the recognition of the fruit fly (B. tryoni). The basic idea of pictorial structure model is to represent an object by a collection of parts arranged in a deformable configuration. We revise the pictorial structure model to include color patterns on the fruit flies. The three yellow color patterns are
represented by rectangles (i.e. PA, PB and PC in Fig. 5(b)) and lines between PA and PC, and PB and PC represent the spatial relationship.

In order to find these three yellow patterns, we firstly locate the middle yellow pattern (i.e. PC in Fig. 5(b)), then locate the top left and right patterns (i.e. PA and PB in Fig. 5(b)). We then rotate the fruit fly to make their long axis (the vertical green line in Fig. 5(b)) vertical to the horizontal line, making the fruit fly symmetric about this long axis in order to efficiently locate the color patterns. The long axis always goes through the middle yellow pattern PC, so we search from the centroid of the image along the long axis in a floating window. The pattern we are looking for is yellow, and it is experimentally proven that the sum of R and G value in the pattern is much greater than other areas and B value is much smaller. We calculate the sum of average R and G values in the window at each iteration. The region that produces the maximum sum value is the yellow pattern in the middle of the body (i.e. PC). The other two patterns (i.e. PA and PB in Fig. 5(b)) are located on the regions above the yellow pattern PC due to the spatial relations among these three yellow patterns. These patterns are located by moving the window along the short axis in a similar way for finding PC.

V. EXPERIMENTAL RESULTS

In the prototype system, the mobile phone in the trap can automatically take the pictures and then upload them to a server via 3G wireless network according a schedule. The detection of invasive flies in the trap is successful with no error occurred in the experiment. For fruit fly recognition on the server side, different color spaces have been tested to detect the yellow patterns of the Queensland fruit fly. A quantitative analysis is given for evaluating the validity of the proposed method for fruit fly recognition based on the color-pattern pictorial structure.

**A. Evaluation of Different Color Space on Yellow Pattern Detection**

HSV and Lab are two color spaces which are widely used in the image processing area because their conformance to human vision. In these two color spaces, H and ab represents the colors, but ab can represent more colors than H. In our case, Lab color space performs better than HSV color space as shown in Fig. 6, because the b component changes from yellow side (positive) to green side (negative). It means that if there exists a yellow color, the maximum value in b component should be yellow. However, yellow is hard to handled in H component [0°,360°].

**B. Evaluation of Fruit Fly Recognition**

The recognition results of the Queensland fruit fly using the proposed method are promising, with most of fruit flies with the yellow patterns around the principal axis detected. The results are quantitatively evaluated using precision calculated using the equation (2):

\[
P = \frac{N_{ofC}}{N_{ofA}}
\]  

where \( N_{ofC} \) is the number of objects which are correctly recognized; \( N_{ofA} \) is the number of the total objects.
In our experiment, 8 out of 10 fruit flies are correctly recognized. The other two flies are not recognized because the quality of the captured images is low so the yellow patterns are too weak to be detected. The overall recognition precision is 80%. Fig. 7 shows some sample results in our experiment.

![Sample results of fruit fly recognition](image)

**VI. CONCLUSION**

The surveillance of insect pests is a challenging problem for agriculture. In this paper, a prototype system for automatic monitoring of fruit flies is developed. This system can be used for data capture, storage, access, and analysis. A trap with Smartphone sensor has been designed and tested. Current experimental results show that the trap is able to capture quality fly images. A simple but effective method is developed for detecting invasive flies in the trap. A recognition program running on the server is then used to recognize the Queensland fruit fly. The prototype is possible to be expanded for monitoring other insect pests.

**ACKNOWLEDGMENTS**

The authors wish to acknowledge support from Microsoft, Queensland State Government, Telstra and QUT.

**REFERENCES**


