Early Pest Detection in Greenhouses

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Abstract

We promote in situ early pest detection in greenhouses based on video analysis. Our target application is the detection of bio-aggressors on plant organs such as leaves. The goal of this work is to define an innovative decision support system, which handles multi camera data and follows a generic approach to adapt to different categories of bio-aggressors. This approach is non-destructive and non-invasive. It will allow producers to take rapid remedial decisions. The major issue is to reach a sufficient level of robustness for continuous surveillance. To this end, vision algorithms (segmentation, classification, tracking) must be adapted to cope with illumination changes, plant movements, or insect characteristics.

The first prototype of our system is under test in a rose greenhouse equipped with five wireless video cameras. The currently implemented algorithms target the detection of white flies and aphids. We present preliminary results for insect detection on sticky traps.

Keywords*: greenhouse monitoring, video data, insect detection, classification, and counting*

1 Introduction

Inside a greenhouse, attacks from insects or fungi are fast and frequent. This implies almost immediate decisions to prevent irreversible pest proliferation. Integrated Pest Management promotes prophylactic, biological and physical methods to fight bio-aggressors while minimizing the use of pesticides. This approach is promising but requires frequent and precise observations of plants that are not compatible with production constraints.

Since the cost of video cameras is decreasing, it becomes realistic to equip greenhouses with such sensors. We thus propose an automatic system based on video analysis for *in situ* insect detection, classification, and counting. We rely on past experience in white fly detection on static images [1] and in video analysis for other purposes, such as video surveillance [2]. We have developed a generic approach based on *a priori* knowledge and adaptive methods for vision tasks. This approach can be applied to insect images in order, first, to automate identification and counting of bio-aggressors, and ultimately, to analyze insect behaviors.

Traditional manual counting is tedious, time consuming and subjective. During the last decade, researches have focused on video applications for automatic surveillance of biological organisms: e.g., [9, 5] for insect behavior recognition. Most of these systems work in constrained environments where camera work conditions are controlled. By contrast, we aim at monitoring insects in their natural environment (greenhouses). To this end, vision algorithms (segmentation, classification, tracking) must be adapted to cope with illumination changes, plant movements, or insect characteristics.

2 Proposed Approach

Our work takes place within the framework of cognitive vision [4]. We propose to combine image processing, neural learning, and *a priori* knowledge to design a system complete from video acquisition to behavior analysis.

We set up a first experiment with a network of five wireless cameras in a rose greenhouse. The position, number, and nature of video cameras are critical to obtain an optimized video sampling in terms of cost/accuracy. In this experiment, we choose to position the video cameras uniformly in the horizontal plane in order to optimize the horizontal sampling in terms of canopy area covering.

The video cameras currently observe sticky traps in order to detect flying insects. In a second time, we plan to focus other video cameras directly on plant organs as recommended by agronomic expertise, e.g. on growing stems for early detection of mature white flies.

Our system, named DIViNe[1], is composed of several modules. First, to allow a tractable data rate, an intelligent acquisition process records images only when insect motion has been detected. Then, adaptive programs analyze visual data extracted from images (color, texture, shape, and size) to detect regions that may correspond to insects in different contexts. Classification algorithms select interesting regions, retaining only the ones corresponding to target insects and count them. Finally, we intend to use scenario recognition techniques to analyze insect behaviors such as egg laying or intra-guild predation.

2.1 Adaptive Detection of Insects

The detection of objects in video sequences is usually based on segmentation techniques such as background modeling or subtraction, in order to detect only moving pixels. In a greenhouse, the major difficulty is to deliver robust detection results with respect to lighting changes. These can be due to changing weather conditions or to the rotation of the sun. The consequences at the pixel level are variations of intensity, color saturation, or inter-pixel contrast. At the image level, these changes may affect just a local area (e.g. shadows) or the whole image (back-lighting). Thus it is very difficult to maintain a good background model during a long time.

To cope with these issues, we adopt a cognitive vision approach by endowing our video segmentation algorithms with learning and adaptation facilities. Our goal is to separate the problem of background modeling into more tractable sub-problems, each one corresponding to a specific situation. These situations, called contexts, are defined by the numerical information representing global and local visual characteristics of significant images. Two examples of contexts (sunny and cloudy) are presented in Figure 1. The knowledge of context variations is acquired during a preliminary (off-line) weakly supervised learning stage. Once context variations learned from a representative training image set, learning-based video segmentation algorithms (e.g. mixture of Gaussian, codebook models) are trained to process each context. Then, when a new frame is acquired, its context is identified to select the corresponding background model for segmenting. More details on this approach can be found in [8].

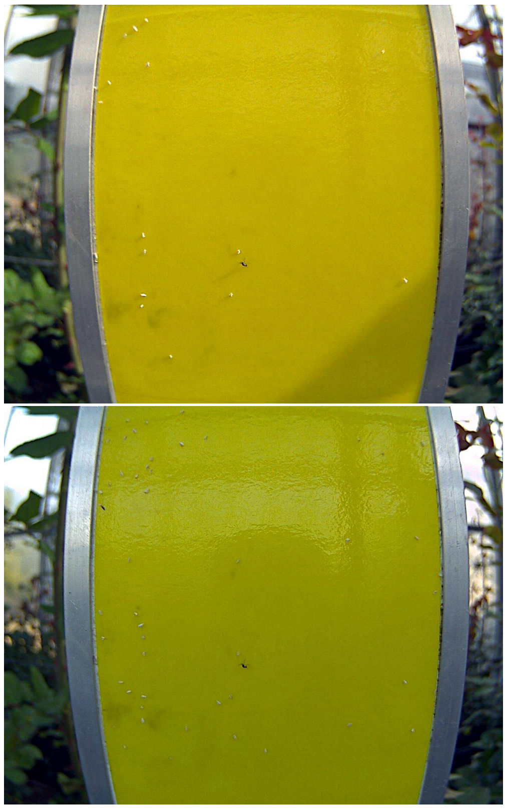

Figure 1. Two different contexts corresponding to different day times.

As seen in Figure 2 insects are better detected with this adaptive approach than with segmentation with fixed parameters.

2.2 Classification and Counting

The role of the classification module of DIViNe is to recognize and to count pests. To this end, it relies on knowledge about insect descriptions and on numerical descriptors provided by image processing programs. We propose a dedicated language to describe this expert knowledge. This language refers to a visual concept ontology [7] which helps experts to describe insects in terms of shape, size, color, and spatio-temporal concepts. Each visual concept

[1] Detection of Insects by a Video camera Network

Figure 2. Exemple of segmentation with (middle) and without (bottom) context adaptation.

is in turn described by a set of fuzzy numerical descriptors. The role of these descriptors is to bridge the semantic gap between low-level numerical values and visual concepts. The corresponding ranges of values are learned from the training set with the help of a domain expert. For example, some values of the HSV color of image areas may be linked with white fly color. Experts use the vocabulary of the general visual concept ontology; for instance, the term “circularity” may characterize the shape of an insect. Currently, we target two classes of typical pests present in the greenhouse: mature white fly and aphids. An example of classification results is presented in Figure 3. If a detected object is not classified into the predefined classes, we store it with its descriptor values for further analysis (e.g. definition of a new class of insect or another moving object). Finally, the DiViNe system returns in real-time two maps of the greenhouse pest infestation (one per pest class). Such maps will be useful for biologists to study the spatio-temporal evolution of populations.

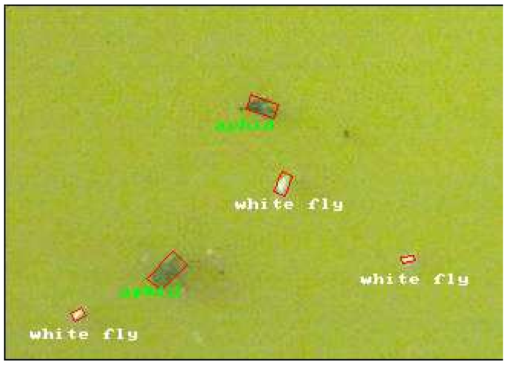

Figure 3. Classification result of detected insects.

2.3 Insect Behavior Analysis

The ultimate goal of our system is to integrate a module for insect behavior analysis. Indeed, recognition of some characteristic behaviors is often closely related to epicenters of infestation. Coupled with an optimized spatial sampling of the video cameras, it can be of crucial help for rapid decision support.

Most of the studies on behavior analysis have concentrated on human beings [3]. In [6], the authors summarize an attempt to extend cognitive vision systems to monitor non-human activities such as insect parasitoid activities.

We intend to use scenario models based on the concepts of *states* and *events* related to intertesting *objects*. A state is a spatio-temporal property valid at a given instant and stable on a time interval. An event is a meaningful change of state. A basic scenario is a combination (e.g. sequential or parallel) of primitive (that is directly detected by vision algorithms) states and events. Basic scenarios amy be considered as higher level states or events and combined to form more complex scenarios. Logical, spatial or temporal constraints between objects, events and states may complete a scenario. To describe the scenarios relative to white fly behavior, we shall adapt a previously defined generic declarative language relying on a video event ontology [10]. For instance, in order to recognize egg laying behavior, we may propose a scenario based on the following description given by experts: ”the female inserts its rostrum in the tissues to lay eggs and, using it as a pivot, deposits its eggs regularly. She lays a circular pattern of eggs on the underside of newer leaves located in the upper portions of the plants" (see Figure 4). This scenario might

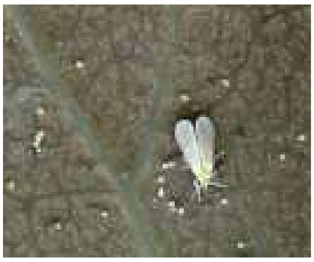

Figure 4. A white fly laying its eggs.

be formalized as follows:

Primitive state: *insideZone*(Insect, Zone)
Primitive event: *exitZone*(Insect, Zone)
Primitive state: *rotating* (Insect)
scenario: **WhiteflyPivoting** (Insect *whitefly*, Zone *z*)
{
A: *insideZone*(*whitefly*, *z*) // B: *rotating*(*whitefly*);
constraints: duration(A) > duration(B);
}
scenario: **EggAppearing** (Insect *whitefly*, Insect *egg*, Zone *z*)
{ *insideZone*(*whitefly*, *z*) then *insideZone*(*egg*, *z*); }
main scenario **Laying**(Insect *whitefly*, Insect *egg*, Zone *z*)
{
{
WhiteflyPivoting(*whitefly*, *z*) //
loop **EggAppearing**(*egg*, *z*) until
exitZone(*whitefly*, *z*);
}
then send("Whitefly is laying in " + *z*.name);
}

3 Conclusion and Future Work

In this paper, we propose an automatic system going from acquisition to behavior recognition of insects in their natural environment. A key-element of our approach is genericity at each level (detection, classification, etc.). DIViNe currently detects few types of pests (mature white flies, aphids). Our final goal is to cope with most of the common greenhouse crop bio-aggressors. Thanks to our extensible software architecture, it should be easy to introduce new types of pests to detect. Our approach is a step toward cognitive vision by combining different complementary techniques (video image processing and understanding, machine learning, *a priori* knowledge) to achieve real time robust detection and recognition.

From a biological point of view, such a system will be able to detect low infestation stages because it allows a continuous surveillance during daylight which favors rapid protection decisions. The second objective of our system in the long term, is to provide biologists with new knowledge to analyze bio-aggressor behaviors. A key step will be to match numerical features (based on trajectories and density distributions for instance) and their biological interpretations (e.g., predation or center of infestation). To this end, we also aim at extending and improving our camera network to monitor plant organs such as young leaves where such scenarios usually occur.

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