# O.50 - Towards a video camera network for early pest detection in greenhouses

Martin, V.[1], Moisan, S.[1], Paris, B.[2], Nicolas, O.[2]

[1] INRIA Sophia Antipolis Méditerranée, PULSAR team, 2004 route des Lucioles, BP 93, F-06902 Sophia Antipolis
[2] CREAT, Chambre d'Agriculture de Nice, 458 route de Gattires, F-06110 La Gaude

Contact : Vincent.R.Martin@sophia.inria.fr, Sabine.Moisan@sophia.inria.fr, bparis@alpes-maritimes.chambagri.fr, onicolas@alpes-maritimes.chambagri.fr

## Abstract

In this paper we promote early bioagressor detection in greenhouse crops in order to reduce pesticide use. Our target application is the detection of pests on plant organs such as rose leaves. Static imagery vision systems used in greenhouse experiments are limited by their spatial and temporal sampling abilities. The goal of this work is to define an innovative decision support system for in situ early pest detection based on video analysis and scene interpretation from multi camera data. This non-destructive and non-invasive approach will allow rapid remedial decisions from producers. The major issue is to reach a sufficient level of robustness for a continuous surveillance. To this end, vision algorithms (segmentation, classification, tracking) must be adapted to cope with illumination changes or with plant movements. The first prototype of our decision support system is being tested in a rose greenhouse with five wireless video cameras. The algorithms currently implemented target the detection of white flies and aphids. We present preliminary results for insect detection on sticky traps. We follow a generic approach to design a system easy to adapt to different categories of bioagressors.

## Context of the Study

Considering temperature and hygrometric conditions inside a greenhouse, attacks (from insects or fungi) are fast and frequent. This implies almost immediate decision-taking to prevent irreversible proliferation. Our goal is to define a new system for in situ early pest detection based on video analysis. Since the cost of video cameras is decreasing [1], it becomes realistic to equip greenhouses with such sensors. We can rely on our past experience in the detection of mature whiteflies based on static images [2]. In this first prototype, we developed an automatic image interpretation system combining image processing, neural learning and knowledge-based techniques. Table 1 compares this prototype to a manual method, and to the expected outcomes of our new system, named DIViNe[1].

---

[1] Detection of Insects by a Video camera Network

| | Manual method | Automatic system (static images) | DIViNe system (video sequences) |
|---|---|---|---|
| Result delivery | Up to 2 days | Several hours | Near real-time |
| Advantages | Discrimination capacity | Accuracy independent of time spent | Autonomous system, temporal sampling |
| Disadvantages | Need of a specialized operator (taxonomist); precision vs time | In the prototype [2], only one type of pest | Predefined insect types; camera installation |

Table 1. Method comparison for identification and counting of pests in a greenhouse.

During the past decade, researches have focused on video applications for biological organism surveillance, e.g. [3] for insect behaviour recognition. Most of these systems work in constrained environments where camerawork conditions are controlled. As an improvement, we propose an in situ vision-based system to continuously survey a greenhouse by setting up a network of Wifi video sensors. We thus intend to automate pest detection, in the same way as the management of climate, fertilisation and irrigation which are carried out by a control/command computer system [4].

## Material and Methods

The agrosystem is a 130m2 greenhouse planted with three varieties of roses and equipped with an opening roof, heating and a fog generator. We want to use integrated pest management methods (prophylactic, biological and physical ones) to fight crop bioagressors (pests) while minimising the use of pesticides.

We set up a first experiment with a network of five wireless cameras (protected against water projection and direct sun) in the greenhouse. The AXIS 207MW video cameras we used provide a high image resolution (1280×1024 pixels) at 10 frames per second. Video acquisition allows continuous survey and detection during daylight which favours rapid protection decisions. The positions, number, and nature of video cameras are critical to obtain optimised 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 optimise the horizontal sampling in terms of canopy area covering. To allow a tractable data flow on the network, we propose an intelligent acquisition process that records images only when an insect motion is detected. Currently, the video cameras observe sticky traps in order to detect flying insects. In a second phase, we intend to locate other video cameras directly on plant organs as recommended by agronomic expertise, e.g. on growing stems for early detection of mature whiteflies. The complete system is described in Figure 1.

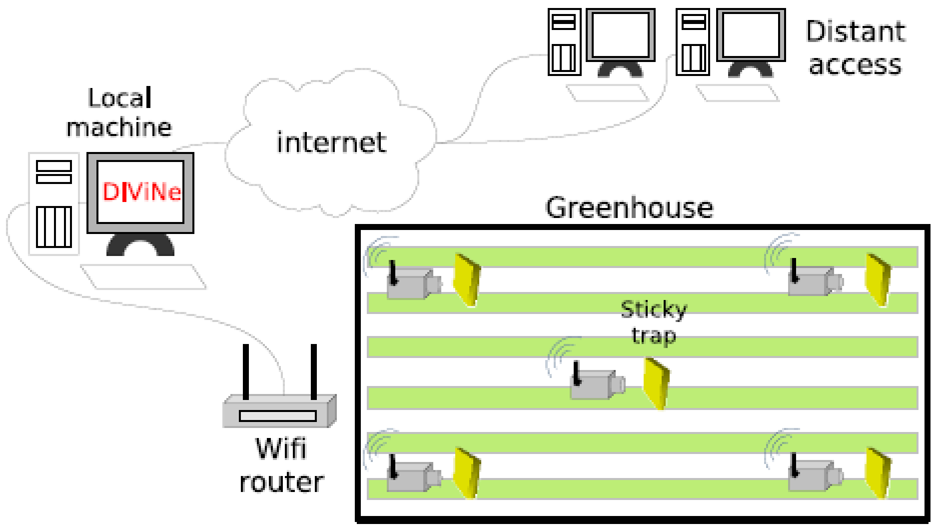
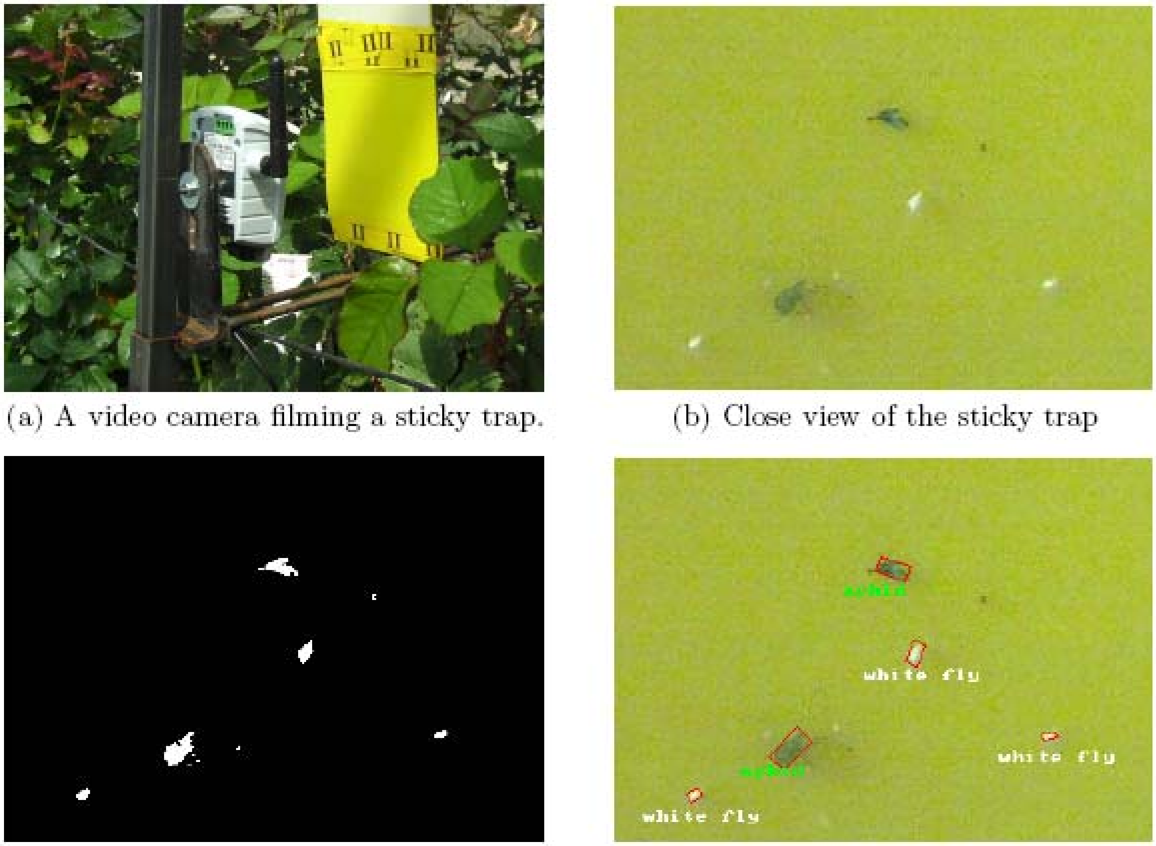



Fig. 1. Overview of the DIViNe system and the wireless video camera network.

The acquired data are then processed: we use video analysis algorithms combined with a priori knowledge about the visual appearance (e.g., shape, size, colour) of insects to detect them. The first objective is to detect and track bioagressors. In our case, the objects of interest are small, complex and they evolve in a dynamic environment.

We are developing adaptive vision methods at different levels (acquisition, detection, and tracking) to provide robust results: segmentation and classification should be able to cope with illumination changes during daytime and tracking algorithms should accommodate plant movements. For instance, we introduced contextual parameter tuning for adaptive image segmentation, which allows us to efficiently tune algorithm parameters with respect to variations in leaf color and contrast. We also intend to enforce adaptability by incremental learning techniques, e.g. to learn the visual appearance of pests.

Our first results are presented in Figure 2.




(a) A video camera filming a sticky trap.

(b) Close view of the sticky trap

(c) Detection results: regions of interest are in white

(d) Classification results: regions are labeled according to the insect types.

Fig. 2. From in situ acquisition to classification of detected insects.

## Conclusion

DIViNe currently detects few types of pests (mature whiteflies, aphids), but within two years we intend to detect most of the common greenhouse crop pests. Such a system can detect low infestation stages, which helps producers to rapidly decide on possible treatment.

Our software architecture is extensible and reusable, so it is easy to add new types of pests to detect. Our approach combines different complementary techniques (video image processing and understanding, machine learning, a priori knowledge) to provide a robust and versatile system working in real time.

In the long term, we want to investigate data mining for biological research. In-deed, biologists require new knowledge to analyse pest behaviours. A key step will be the ability to match numerical features (based on trajectories and density distributions for instance) and their biological interpretations (e.g., predation or centre of infestation).

## References

[1] Wang, N., Zhang, N.,Wang, M.: Wireless sensors in agriculture and food industry–recent development and future perspective. Computers and Electronics in Agriculture 50(1) (2006) 1–14

[2] Boissard, P., Martin, V., Moisan, S.: A cognitive vision approach to early pest detection in greenhouse crops. Computer and Electronics in Agriculture (2007)

[3] Noldus, L., Spink, A., Tegelenbosch, R.: Computerised video tracking, movement analysis and behaviour recognition in insects. Computers and Electronics in Agriculture 35(2) (2002) 201–227

[4] Ehret, D.L., Lau, A., Bittman, S., Lin, W., Shelford, T.: Automated monitoring of greenhouse crops. Agronomie: Agric. Environ. 21(4) (2001) 403–414

## Acknowledgements

We thank P. Boissard and all the CREAT staff for their participation in this work.