Pests detection system for agricultural crops using intelligent image analysis

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***Abstract*— The paper proposes an intelligent method for real-time monitoring of the evolution of pests in an agricultural crop. The system consists of a pheromone trap, a camera that periodically fetches frames with trap and a data transceiver module where the frame is encapsulated with the date and station id. The data arrives at a server where they are retrieved and analyzed using two deep learning artificial neural networks. One determines the type and number of pests and the other identifies the evolution of the pest population. The system has been experimented with an apple tree culture in order to early identify pests and combat them.**

Keywords*— *Image analysis, deep learning artificial neural network (DL-ANN), pheromone trap, pest detection

I. Introduction

Along with hydric stress, stress caused by pests is one of the major risk factors in agricultural crops. In the context of current climate change, the pests have adapted to new thermal conditions, to atmospheric and to soil humidity resulting in more resistant species. More research papers support the monitoring of pest evolution by sampling over shorter time intervals, reaching some species in real-time to apply pest control measures in time [1]. In the elaboration of this paper, knowledge of electronic monitoring systems and artificial intelligence but also methodologies for the detection of pests using pheromones traps were needed. As shown in the literature, the number of pests present in a pheromone traps in a time of between a few hours to a day is equivalent to the number of pests that are present in a crop in an interval of a few days [2]. Detection of pest evolution over a time span of several days involves the timely application of combat measures to different cultures and different environmental conditions. Our proposed solution uses the pheromone trap for a species of apple tree pests (cidia pomenella) and a real-time monitoring method using the video camera and intelligent image analysis algorithms.

The use of volatile substances obtained from fruits as attractants for the parasitic species cidia pomenella is treated in the paper [3]. It has been observed that the use of esters synthesized from fruits are attractive especially for butterfly males but also for young females. The study shows that a relatively small amount of such synthesized pheromones attracts a large number of parasitic insects. Such substances are used in the construction of traps. Their initial role is to reduce the number of the population but then they have been used as indicators of the activity of parasitic insects in a culture, as shown in the paper [4]. The need to identify as accurately as possible the times when the number of individuals captured in pheromone traps has increased greatly has led to the introduction of monitoring with the capture and transmission of images of the state of the trap, images that can be studied subsequently, from a distance - as it is shows in the work [5]. In the same paper, the emphasis is how the performance of the trap is affected by placement of the video monitoring solution and to demonstrate that the intervention on the trap by adding an electronic device does not reduce the number of insects captured by it. In the paper [6] it is shown that images with insects in pheromone traps can be analyzed and thus a series of information regarding their size, degree of maturity or number can be obtained.

In this paper we present a solution that includes harmful insect capture techniques to fruit tree crops using ester-synthesized pheromones, automated monitoring techniques using video cameras and image classification techniques with captured insects and analyzing their evolution using intelligent algorithms (neural networks). The solution allows identification of pests inside the trap, counting them and identifying how they evolve over time. First DL-ANN is used to recognize pests in the pheromone trap and the identification of pests from different other insects, organic or inorganic fragments which may be accidentally present in the trap. Also, their evolution in the pheromone trap for a period is identified using second DL-ANN. Such identification helps determine the effects of chemical methods of pest control but can also be used to determine the effectiveness of some non-synthetic, natural pest control methods that are increasingly being investigated at the time. The novelty elements brought to the paper are related to the intelligent method of analysis of the frames take with video camera from pheromone trap and the use of two levels of recognition using deep learning artificial neural network: recognition of the type and number of pests and pattern recognition for a positive evolution in the population of pests.

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II. System Block Diagram

The figure below (fig.1) shows the system diagram. It is composed of an on-site monitoring station and a central server, which collects the data from the station.
The monitoring station consists of a trap of synthetic pheromones (based on fruit extracted esters), a video camera, the logic of extracting information from the room (integrated in camera) and an XBee transceiver.
The server has a gateway through which the information from the station is received, a server-side application responsible for fetching events (data) and storing them (Complex Event Processing module - CEP), a level 2 server-side application responsible for recognizing images and classifying insect species and a level 3 server side application responsible for extracting data on the evolution of harmful insects.
On the pilot we implemented was used a single station that monitors the evolution of the moth butterfly of the apple crop. XBee communication allows multiple endpoints (stations) to be connected to a central collector (server). So, the system can be extended, if desired, with more stations.

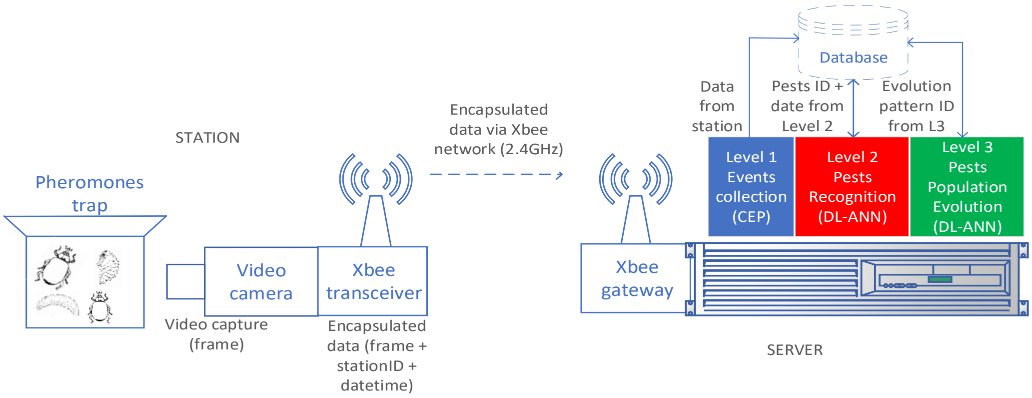

Fig. 1. System block diagram (station with pheromone trap and video camera to the left and server station with two levels DL-ANN to the right).

The central component of the station is a video camera. Characteristics are: visible resolution 1944x1092, focal length 4 mm, F2.1, IR night vision 35 m, thermal vision resolution 160x120. H.264/MJPEG, outdoor operation.
The camera allows commands from an external system (for automating tasks). The camera supports both visible and near IR (night vision) and far IR (thermovision) views. It is operable under out-door conditions (supports IP 67 standards).
At the station level, a camera control logic has been developed that automates a snap photo task, converting them to monochrome format and highlighting the image outline - all these operations are done at the camera level by internal commands. The station has an integrated 2.4 GHz free XBee communications system. In the open field, planted with fruit trees by placing the monitoring station at the level of the crown and under the conditions in which the receiver and the server are placed on a hill above the orchards, the coverage area of our pilot is 1 km..
There is also a 13A / h 12V battery responsible for supplying the system. During the day the battery is charged from a 32V / 250W photovoltaic panel. The system has an energy autonomy during the seasons of spring (April, May), summer (June, July, August) and autumn (September, October)..
The images are transmitted via Xbee to the server. In order to be able to transmit in a reasonable time (XBee is a communication optimized for low power consumption, so it has a reduced bandwidth) unnecessary details are eliminated from the images: the image is converted from color into gray levels (8 bits) then in monochrome with highlighting the contours of objects (added over image). Thus, the figure below illustrates the initial images (captured by the camera) and processed, ready for transmission.

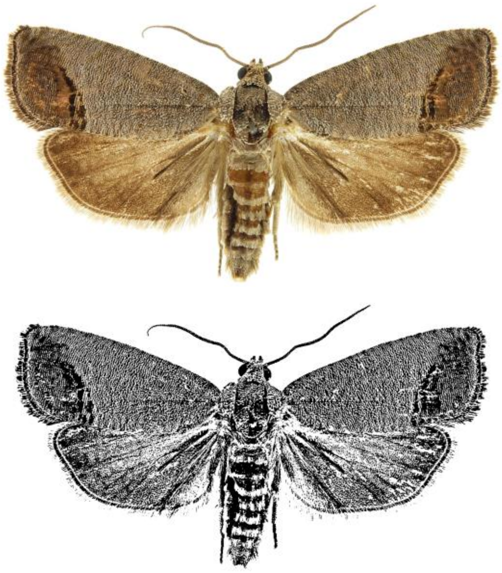

Fig. 2. Original photo (1300x722) with size of 365kB and final photo (same resolution) with black and white and shape with size of 84kB. This primary processing of image is performed at station level so when transmitting to XBee to have only details which are needed to secondary processing at the server level.

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The images are captured at motion detection event at the level of the trap but not more often than 3 minutes.

The images from the station reach the server level. Here we have the gateway - an XBee transceiver identical to the one used at the station. The difference is given by the board on which the XBee shield is installed - an 802.15.4 Gateway USB SMA 5 dBI USB converter.

The data (images) are taken over the USB port by the Complex Event Processing (CEP) component running on the server. This is a software component specialized in listening on a port and on a set path (in our case on the USB port), in taking over the data packets, preprocessing them to be converted into a data structure, in real-time processing of the data: filtering according to certain values, setting time windows, setting measurement windows (number of measurements) and storing them in a database. In our case, the flowchart below shows the CEP-level processing that is performed on the data (images) coming from the station.

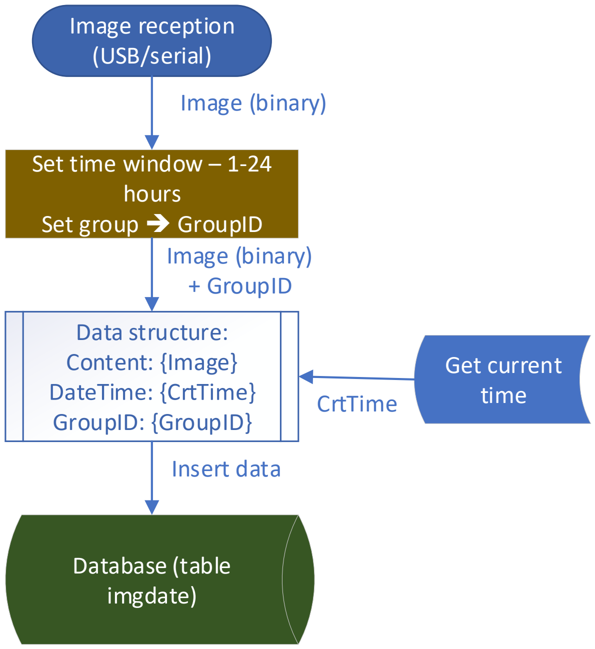

Fig. 3. Processing at CEP level. 1 hour time window is required to group more pictures. Thus it can be built a time evolution of the population of pests

The data stored in the database then reaches the next module - the intelligent processing module (level 2 of processing). Its purpose is for each record in the table below to identify the presence of the butterfly apple moth in different stages of evolution. For this a deep learning artificial neural network (DL-ANN) was used. An input neuron is given by a 64-bit number which is the equivalent of 64 monochrome processed image pixels (a long type number). The total number of neurons in the input layer is 14666 but they are grouped into 733 lines (20 numbers / pixel line). The hidden layer contains 256 neurons and the output layer contains 4 neurons - each shows the number of harmful insects captured at different stages (larva 1, larva 2, adult 1, adult 2).
The test results are stored in the level1result table in the database. The format is shown in the table below:

TABLE I. STRUCTURE OF LEVEL1RESULTS TABLE FROM DB

Field	Type
Pests stage 1	Number – long
Pests stage 2	Number – long
Pests stage 3	Number – long
Pests stage 4	Number – long
GroupID	UUID
Datetime	Timestamp

The data in this table represent inputs for the next level of intelligent analysis: detecting population evolution. And here a DL-ANN neural network is used. As entries we have the records of a group. These may vary depending on the time window that has been allocated for that group and depending on the frequency of events (insect detection within the room radius). The size of a group can range from 1 to 1440 records.
The hidden layer is 200 neurons and the output layer consists of 2 neurons that indicate the positive or negative evolution of the population.

III. RESULTS

The application has integrated an AI core, the Deep Learning Artificial Neural Network. The recognition of patterns is done on two levels: patterns for identifying pests at various stages of evolution and patterns to identify pest population evolution. Analysis of the pheromone trap implies a determination of the course it will have at the level of the entire crop.

The following sets of patterns were used for the two neural networks when training the network (Table 2).

TABLE II. NUMBER OF PATTERNS USED FOR SUPERVISED LEARNING

DL-ANN Level 2	
Pattern type	**Number**
Pests stage 1	15000 (500 / 1-30 indiv.)
Pests stage 2	15000 (500 / 1-30 indiv.)
Pests stage 3	15000 (500 / 1-30 indiv.)
Pests stage 4	15000 (500 / 1-30 indiv.)
DL-ANN Level 3	
Pattern type	**Number**
Positive - evolution to stage 2	6000
Positive - evolution to stage 3	12000
Positive - evolution to stage 4	11000
Negative – not evolution	11000

The patterns were obtained from several sources. First, some of the patterns with images of individuals in different stages were taken from the existing photo libraries within the

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beneficiary Institute (200-300 for each stage and each number). Another part was obtained as a result of the 5-month monitoring that took place last year (100 / number of species + about 1000 for each evolution). Finally, a significant part was automatically generated, through cloning at the image level - the rest of the templates.

The learning is done in 20 epochs, the optimizer is a downward stochastic gradient and the activation function is of the RELU type (if the input is below a threshold it will be 0 otherwise the value of the input)..

The table 3 presents the results obtained by training DL-ANN using patterns with pests at various stages.

In figure 4, there are various evolutions charts for the pests present in the pheromone trap. Simple determination of the number of pests is not always relevant to determine a positive or negative evolution of the pest population.

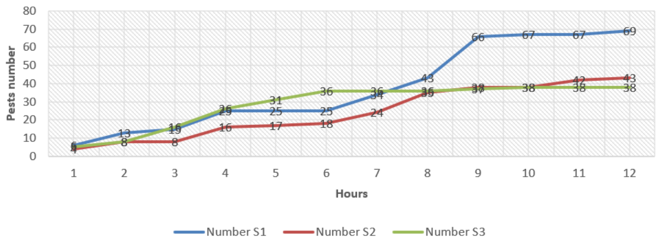

Fig. 4. Evolution of pests' population for 3 different series. Level 3 DL-ANN can identify positive or negative population evolution patterns. In this figure, blue and red charts are positive evolutions and green is negative evolution even if at 5- and 6-hour the number of pests in trap is bigger for green chart

The testing of the system led to the correct identification of the positive type developments in over 97% of the cases - at a test rate on 30% of the training templates we have a total of 12000 tests.
The percentage of correct answers is given in Table 4.

TABLE III. PATTERNS USED FOR TRAINING LEVEL 2 DL ANN - PESTS RECOGNITION

Cidia pomenella patterns (examples)	DL – ANN output (Learning phase)
	Adult pattern 1: 20 epochs / 96%
	Adult pattern 2: 20 epochs / 94%

TABLE IV. RESPONSES (CORRECT)

Test type	Correct responses (%)
Positive - evolution to stage 2	97.453
Positive - evolution to stage 3	97.322
Positive - evolution to stage 4	97.441
Negative – not evolution	98.13

IV. CONCLUSIONS

The solution proposed by us brings as a novelty the determination, using artificial neural networks, of the number of harmful insects (by identifying their form in the pheromone trap) and the determination of how their population evolves. The additional element - determining the evolution of the population is important by eliminating false positive alarms - there may be moths at one point but, due to the different climatic conditions, they do not evolve to reach a population dangerous to the culture. Another utility for determining population evolution is for further studies of how the pest population can be controlled..

As future directions of research are the use of the system to identify other types of pests. The structure of the system remains the same, the training templates change, and the training process is resumed. The obtained current templates were added to the training template library for neural networks.

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REFERENCES

[1] Y. P. Singh and Sudhir Singh, "Impact of mitigation technologies", Indian Farming 68(01): 69–74; January 2018;

[2] S.Arnaud-Haond, I.M.J.Van den Beld, et all., "Two "pillars" of cold-water coral reefs along Atlantic European margins: Prevalent association of Madrepora oculata with Lophelia pertusa, from reef to colony scale", Deep Sea Research Part II: Topical Studies in Oceanography, Volume 145, November 2017, Pages 110-119;

[3] Douglas M. LightAlan L. KnightClive A et. al, A pear-derived kairomone with pheromonal potency that attracts male and female codling moth, Cydia pomonella, Naturwissenschaften, August 2001, Volume 88, Issue 8, pp 333–338

[4] D.E. FernáNdez, L. CichóN, S. Garrido, M. Ribes-Dasi, J. Avilla, Comparison of lures loaded with codlemone and pear ester for capturing codling moths,Cydia pomonella, in apple and pear orchards using mating disruption, Journal of Insect Science, Volume 10, Issue 1, 2010, 139

[5] Adriano Guarnieri, Stefano Maini, Giovanni Molari, Valda Rondelli, Automatic trap for moth detection in integrated pest management, Bulletin of Insectology 64 (2): 247-251, 2011

[6] P. Boniecki; K. Koszela; H. Piekarska-Boniecka; K. Nowakowski; J. Przybył; M. Zaborowicz; B. Raba; J. Dach, Identification of selected apple pests based on selected graphical parameters, Proceedings Volume 8878, Fifth International Conference on Digital Image Processing (ICDIP 2013); 88782S (2013)

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