Basic Algorithms for Bee Hive Monitoring and Laser-based Mite Control

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***Abstract*—The work in progress described in this paper has the objective to implement a beehive monitoring system to monitor essential parameters of a bee hive (such as temperature, sound, weight) and additionally including an image recognition algorithm to observe the degree of infestation with Varroa mites. Mites should be detected at the entrance and statistics about the degree of infestation should be made available by a web interface. As ultimate approach to fight mites without chemicals the coordinates of the mites are to be detected and a laser will be used to kill them. This work describes approaches relevant to all steps of the aforementioned procedure, however it is still work in progress and the components of the approach still have to be integrated into one system that is deployable in practice.**

I. Introduction

Bees have been disappearing at an alarming rate and continue to vanish without a specific reason. Honey bees are of major importance to the humanity, being a central entity in nutrition and agriculture. The western honey bee (Apis Mellifera) is responsible for the pollination of approximately 100 types of crops and plays a role in a range of human activities, including nutrition, medicine, agriculture, and social studies.

Major factors threatening honey bee health are parasites and pests, pathogens, poor nutrition, exposure to pesticides and stress. These factors tend to interact with each other, increasing their complexity and generating potential risks. Varroa destructor was highlighted as a primary factor affecting the health of European honey bee populations, stating that the Varroa mite is "the single most detrimental pest of honey bees, and is closely associated with overwintering colony declines" [1].

To control this parasite, beekeepers apply miticides inside the beehives. However, the currently used miticides can contaminate the honey and wax, making it toxic and interfering with the bees health. In [2], almost 60% of the 259 wax and 350 pollen samples tested, contained at least one systemic pesticide.

To protect the worldwide food supply it is clear that honey bee populations need to be maintained in an optimal state of health and afforded opportunities to grow. Finding ways to protect the bees from predators and parasites without causing collateral damages to their health and without adding toxic elements to their honey is an important open issue. One solution that can protect bees from mites relies on laser beams. They can be used for killing the parasites or predators after visual recognition without damage to the bees. Also, through the use of sensors, it is possible to gather data unobtrusively and analyze these data to gather information and provide a unique picture of the conditions in the beehive in real time. This information is very useful to help the final users (beekeepers).

The system, however, has to be intelligent and fast enough to accurately detect the invader and kill it without collateral damages, tracking the objects of interest and controlling the laser intensity and the target location with precision. To achieve this, it is necessary to apply the right computer vision techniques to identify properly if there is an invader (either a mite or other harmful animal trying to enter the hive) as well as the algorithm has to manage properly the response of the laser to a previous detection.

This work presents a system composed by image processing techniques and hardware to identify and track mites in honey bees. Also, it introduces the present work in progress which aims to improve the results obtained in previous works to deliver an optimal final solution. The goal is to provide a solution composed by monitoring, detection and threat control that can be feasible and low-priced.

II. Related Works

Using data collection to evaluate the conditions of beehives has been a topic of high interest in academia in recent years. In this section, some works concerning monitoring tools, detection of plagues and the use of laser to kill threats are presented and discussed.

Many works in the literature consist in monitoring systems used only to provide information to the final user about the status of the beehives. These works consider parameters collected by sensors such as temperature, pollutants, weight, sound and video, to gather information and plot it into user-friendly charts.

In what concerns to monitoring, HiveTool [3], for example, is an open source project that offers many suggestions of well-suited hardware and provides software that can be adapted by the users and used to monitor hives. The software can read data from sensors, store them in a database and convert them into charts.

Arnia [4] is a proprietary system which sells the whole hardware/software structure and charges a monthly fee to provide information such as weight, temperature, humidity, activity and others through SMS or email alerts to the beekeeper. Other works [3], [5], [6], [7], [8], [9], [10], [11] propose similar systems, differing mainly in the number and type of sensors.

In what concerns to detection of plagues and image recognition, there are multiple algorithms available for object tracking in video sequences varying on techniques and efficiency. The goal, however, is to apply an algorithm that can be fast and also can offer reliability in identifying the right targets.

In [12], an algorithm to detect and track mites in honey bee cells is presented with routines executed in MATLAB. It reached a detection rate between 92.93% and 94.57%. A disadvantage of this work, however, is that the algorithm is executed in standard mainframes. The execution of these routines in portable devices may not be feasible.

In [13], a method to monitor bees using image processing is presented. Images of insects in flight were collected to perform the identification process. After a pre-process, the pixels containing the insects were used for training purposes in a data mining/machine learning tool. The work reached a classification rate of 98.91%. Despite the great results, the work was not tested in a real-time environment as the images were taken to the lab to further classification.

The Hive Project [14] also presents an ongoing project to instrument beehives and help avoid colony collapse. The authors have plans to record numbers of bees entering and leaving the hive, their types, and whether they are carrying pollen or have mites attached. The actual status of the work, although, is not disclosed.

Finally, in what concerns to protection, there is a registered patent [15] which consists in a device that uses laser beams to kill pests after a scanning process. The method or algorithm, although, is not disclosed. Besides that, the working mechanism of this engine is invasive and might be stressful for the bees.

Another work [16] consists in a device equipped with a laser beam and a camera to identify mites in bees and kill them while bees enter the hive. However, this work only considers protecting bees from mites and seems to be a project draft that stills in crowdfunding phase.

A Laser Bug Zapper [17], or photonic fence, was received with some enthusiasm last year when the start of the system's manufacturing was announced. The goal of the system is to fence out harmful mosquitoes from a given area. It is equipped with a 3-watt, 532-nanometer-wavelength green laser to kill the insects. The price of this kind of laser is the constraint of this solution.

In this section, it was possible to have an overview of the existing proposals concerning the three aspects this work aims to approach. There are many available ideas or projects, but the existing works only offer isolated solutions, concerning each one of the aspects separately. A functional laser system for the protection of bees has not been accomplished yet.

The goal of this work is to provide a more complete system, capable of monitoring the beehive and also protect it from possible harms, without being too obtrusive to the bees or too expensive to the beekeepers.

III. Search & Destroy System to protect Bees from Mites

The work presented here consists in the development of two modules for automatic image detection of mites using a camera sensor and a laser. To achieve this, an algorithm implementing Image Processing techniques was developed and applied in different images of bees to successfully identify the mites. Thereby, if a pest is identified, its position can be calculated to orient a laser beam based on this data in a second step, which is to kill the threat automatically.

This section is divided into two subsections that describe each module in more details.

A. Image Recognition

Computational methods to recognize objects or patterns in a picture are getting more and more popular in many important areas, aiding humans in tasks that before could cost a lot of work and time.

Apply image processing to recognize patterns in biomedical images, for example, allows professionals to conclude the diagnosis faster and with higher precision. The ImageJ Framework is an open source Java framework available for many platforms that supports different kinds of image manipulations and operations. ImageJ is being extensively used by scientists around the world to process images, in many different formats [18].

Taking advantage of the power and flexibility of this framework, this first study used ImageJ to evaluate different methods for the recognition of mites in images [19]. Histogram Analysis, Hough Transformation, and Region Labeling/Color Identification were applied to the images in order to investigate the pros and cons of each operation and identify which approach could be applicable for the purpose of this work in detecting mites.

- *Histogram Analysis*: A histogram analysis quickly shows the distribution of the different colors in an image. Experiments have shown that the histogram analysis can be used in order to decide whether mites are present on the current picture or not, by detecting the typical color peaks in the Histogram. Despite the success for the classification of mites are present or not by the analysis of the histograms of images, a serious disadvantage of this method is that the position of the detected mite cannot be derived from the histogram. The histogram analysis can, therefore, be used as part of a larger algorithm as a first step in the classification process. The subsequent steps of the localization, however, must be carried out by another method.

TABLE I
PARAMETERS CONFIGURATION IN THE REGION LABELING ALGORITHM

Parameter	Description
MinSize	Minimum Size of the Region to be labeled
Tolerance	Tolerance in the similarity calculation between two colors
Gamma	Gamma for pre-processing in dark shots
MinRed	Minimum red value in a pixel to be classified as red
MinDistance	Minimun distance between the RGB channels

- *Hough Transformation*: The Hough Transformation is an efficient way of detecting lines and circles on images. However, recognition of mites by their elliptical shape is special due to the high storage demands and intensive computing requirements. There is also a difficulty in parameterizing the form of mites in the application due to the different possible shapes they can assume, considering their positions relative to the camera, and since it's necessary to convert all images in Edge Maps. These disadvantages results with this method not being suitable for this problem.
- *Region Labeling*: Provides a suitable image material and, with some modifications to the basic algorithm, it turns into a promising approach to recognize and locate the mites. It has a good detection speed and a tolerable error rate. It identifies regions inside a color interval. The regions can be checked for size and color, to determine whether it is a mite or not.

Region Labeling/Color Identification has thus been chosen as the operation to be performed in the image processing since it presented the best result for the desired purpose. The algorithm was fed with the necessary parameters to classify an object as a mite in a given image, as shown in the Table I.

With this information, it is possible to determine the size, color, position and shape of a potential mite. To ensure robustness against wrong detections, either by image noise or impurities in the bees, it is essential to define thresholds for all eligible regions. The selection criteria are applied and only the eligible regions, which contain values in the desired thresholds, remain. If the set of regions in this sequence is empty, there is either no infection or the minimum threshold is too high. For this reason, it is essential the correct adjustment of parameters to each particular application.

To perform the tests, images with different characteristics such as different sizes and light conditions have been used, artificially generated or available online. These tests allowed the correct adjustment of parameters in a way that the algorithm could provide correct results.

To examine how the algorithm deals with different exposure levels, adjustments in the gamma parameter were made to test its efficiency in situations of under- and overexposure. The Figure 1 shows the best combinations between gamma values and brightness level to achieve good results in recognition. The *MinRed* and *Tolerance* parameters were both set to 100 in these tests.

Different associations of parameters were tried in order to find the best and worst cases. Variations in the pictures angle

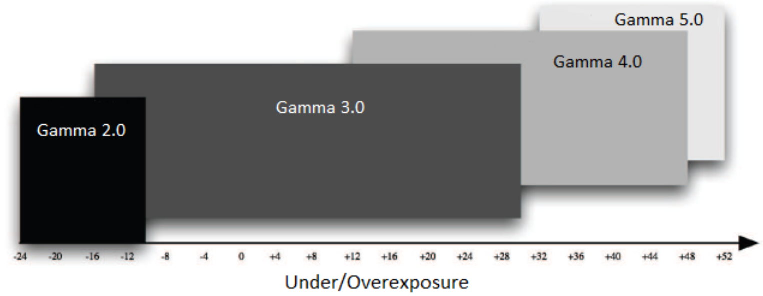

Fig. 1. Different Gamma correction levels combined with brightness

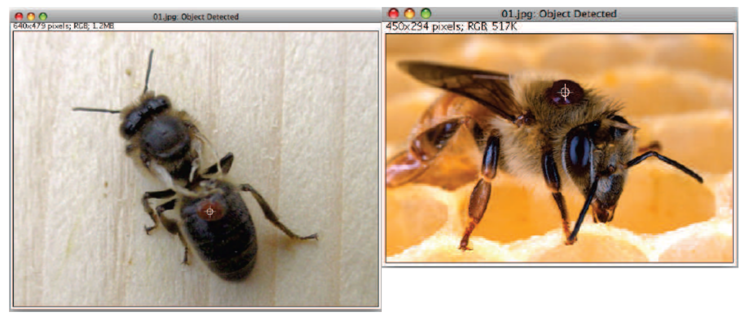

Fig. 2. Detection of Mites in Images with Different Angles

have also been considered in the tests, so it is possible to detect the mites even with different camera positions, as shown in Figure 2.

Since there are different types of cameras available on the market, with various resolutions, the many possible sizes of pictures have also been considered in the tests so the processing speed and the error rate in identifying mites could be evaluated. It is important to remark that the processing speed should be kept as high as possible since it has a direct influence in the response time of the whole system. Therefore, the camera resolution should be adjusted to provide images with an optimal resolution, that could be fast processed.

Figure 3 shows the results of these tests. It can be seen that pictures with smaller sizes tend to have a high error rate and, thus, a great risk of misdiagnosis. The misdiagnosis can be the non-recognition of a mite or an erroneous detection in an uninfected bee. Also, a resolution of 320x240 pixels showed optimal results, since the average processing time is 0.477s and the error rate is around 0%.

B. Laser Structure

First experiments have been conducted in [20], with a solution composed of hardware and software. The prototype consisted of an image recognition module to detect the position of the target and the resultant laser handling. The hardware (Figure 4) consisted in a positioning module (a mechanical apparatus with two structures -vertical and horizontal- connected to each other), and a head composed by a webcam and a laser pointer. Two stepper motors were used, one to move

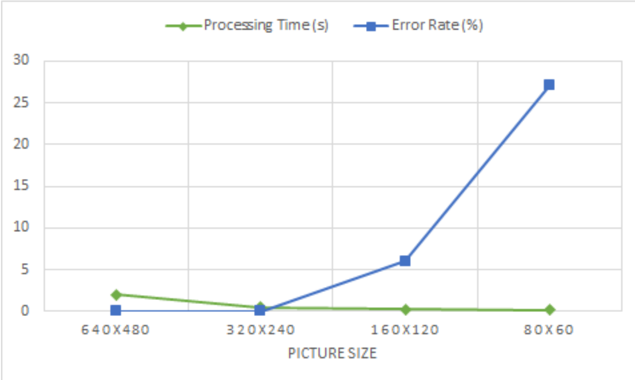

Fig. 3. Error Rate and Processing Time according to Picture Size

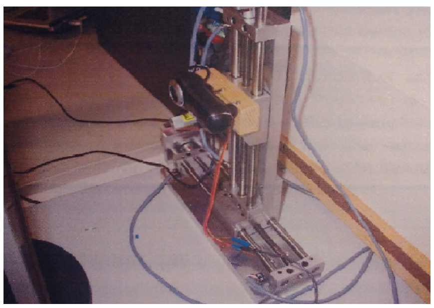

Fig. 4. Vision of the hardware

the vertical structure through the horizontal axis and another one to move the head through the vertical axis.

The software was made in Java and was responsible for coordinating the movements of the head throughout the whole Positioning System after receiving the coordinates from the Image Recognition module, and for managing the power and the use of the laser beam.

To perform the tests, the apparatus was pointed to a TFT screen where another Java software was running, simulating the flight of an infected bee in different trajectories. Despite being a non-realistic approach, the use of the TFT screen to perform the tests was essential since in a real world scenario is way more difficult to evaluate the performance of the system reacting to different flight patterns, flight speeds and so on.

While running, the algorithm's first step is to calibrate the initial position of the head, setting its coordinate values in the system. With these values, it is possible to calculate how much the motor has to work to move the head from its initial coordinates to the given coordinates of detection. After a detection, the algorithm converts the distance in pixels to the distance in centimeters the head has to move to reach the right position. When it reaches the final position, the laser is activated.

The accuracy of the laser was tested according to different simulated trajectories and speeds. The number of times the laser accurately reached the target was evaluated and the error percentage was measured as shown in the chart of Figure 5. It is possible to observe that the round trajectory resulted in the

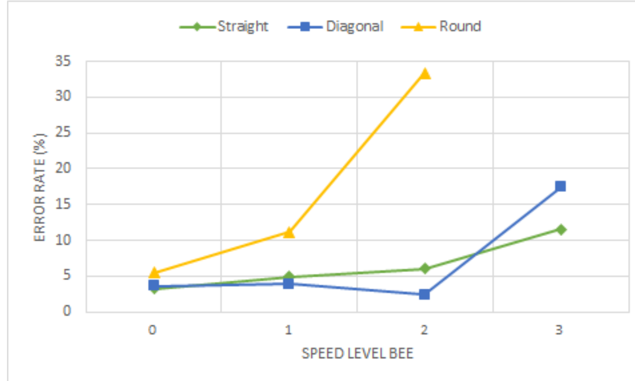

Fig. 5. Error Rate based on the Trajectory Type and Speed

highest error rates, varying according to the speed. With speed 2, the obtained error rate was of 33,33%, from which it was deduced that this rate was already too high to even consider speed 3 as a possibility. The other trajectories until speed 2 presented an error rate below 10%, which is an acceptable error rate for the purposes of this work.

IV. Work in Progress

The present work in progress consists in the development of a new version of the system present in the previous Section for automated image detection of different pests (instead of only mites) using camera sensor and laser technology for a feasible price.

Although the first version has similar goals, it is not realistic enough and it was never tested in the real world. With real field tests, it is possible to verify the actual problems of the system to improve it, so it can work properly. To allow this "real world implementation", it is also important to make use of portable processing units. With the advent of cheap single-board computers, Raspberry Pi 3 [21] is a good choice to run a wide range of different applications that need, mainly, portability and some processing power.

In this new system, the detection speed should be kept as low as possible and should not require high-level computational capacity, as now the system is running on a portable platform.

The camera is positioned above the entrance of the hive and the generated images are evaluated using the network. Herein, if a pest is identified, the position of the pest can be calculated to orient a laser beam based on this data in a second step, which is to kill the threat automatically, as pictured in Figure 6. Also, an information system is being developed to collect essential everyday data from different sensors that may be installed in the hive, and generate user-friendly charts to the beekeepers.

The three main subdivisions of this work are: the image recognition algorithm to identify the pest; the laser beam management algorithm to control the intensity of the beam and its position; and the information system to support the final user.

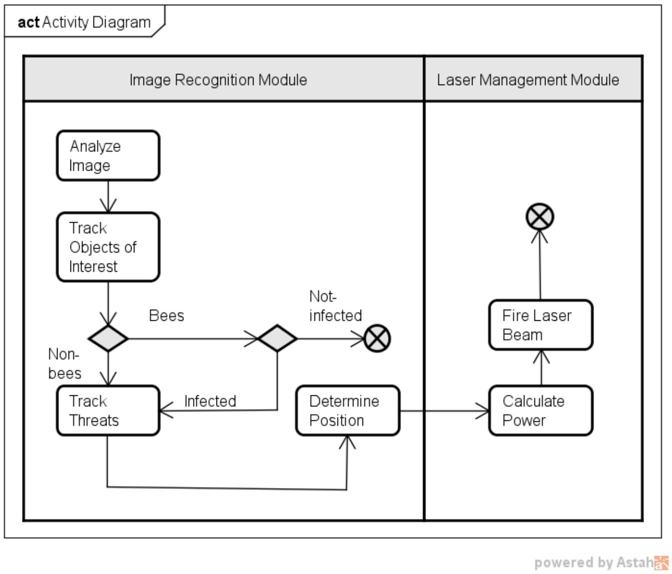

Fig. 6. Activity Diagram of the Image Recognition and Laser Modules

A. Image Recognition

Convolutional Neural Networks (CNNs) were responsible for major breakthroughs in Image Classification and are the core of most Computer Vision systems today. They differ from common Artificial Neural Networks (ANNs) because they consider the spatial structure of the images. CNNs are used in a variety of areas, including image and pattern recognition, speech recognition, natural language processing, and video analysis.

A CNN consists of one or more convolutional and sub-sampling layers, which are followed by one or more fully connected layers as in a standard ANN. It treats input pixels which are far apart and close together, detecting the same features in different parts of the image. As the same coefficients are used across different locations, the memory requirement is considerably reduced.

In object tracking, these networks can learn in which regions of the image the desired targets are. Through different learning techniques, they are trained to approximate results as much as possible to the given patterns. In traditional models for pattern recognition, feature extractors are hand designed to find objects according to the specified rules in the code. In CNNs, the weights of the convolutional layer used for feature extraction as well as the fully connected layer used for classification are determined during the training process.

Each feature-detecting neuron in a layer receives a set of features located in a small neighborhood (varying according to the chosen kernel size) in the previous layer as inputs. With these local receptive fields, features can extract elementary visual features, such as edges and corners, which are then combined by higher layers. Convolution filter kernel weights are decided on as part of the training process.

The convolution operation extracts different features of the input. The first convolution layer extracts low-level features

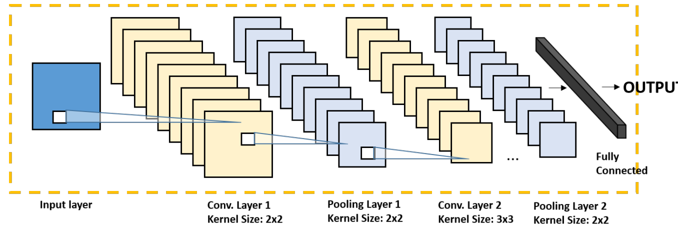

Fig. 7. Visual representation of an used CNN

like edges, lines, and corners. Higher-level layers extract higher-level features. The pooling layer reduces the resolution of the features, making them robust against noise. The last step is to use fully connected layers as the final layers of a CNN. These layers sum a weighting of the previous layer of features, and can determine an output as result. Figure 7 shows one of these CNN models used in this work.

Caffe Framework is a deep learning framework developed by Berkeley Vision and Learning Center [22] and used in a range of vision, speech, and multimedia computational applications. This work used Caffe as framework, to create convolutional networks capable of learn with the given images and identify the desired targets. In the first phase, with a training data set of 5000 artificially generated images and a training period of a few minutes, the network reached an average detection rate of 72%. This first step was only used to make preliminar tests of infected and non infected bees.

However, to achieve a superior accuracy and to perform object detection, CNNs with different configurations were tested. The networks were trained through the use of a dataset consisting in artificially generated images and also images retrieved in google image search, containing infected and non infected bees. The images were then manually labeled to determine the ground truth in each one of them and generate the desired outputs. In the output image, the brightness value of pixels where a desired target is (region of interest - ROI), is equal to 1. The pixels that do not contain the target, outside the ROI in the image, have a brightness value equal to 0. Therefore, the brightness value of pixels in the output image is the probability of that pixel belonging to the desired object.

These input and ouput images were used to feed the network. When the train was finished, the network was applied to another dataset to find the connected components. In Figure 8, the right image is the input, the middle image is the output and the left image is the successfully detection after the training process. In this second step, the network reached a detection rate of 93%.

To have a better overview of the accuracy of the results, the network was tested in videos taken from the available camera on the first system prototype installed in the beehive used as a case study in this work. Figures 9, 10, and 11 present the original frame and the output obtained after the network inspection. The red areas show the matches with the objects of interest. As closer the color of the filter is to red, higher are the chances of a detected object of interest. The first test

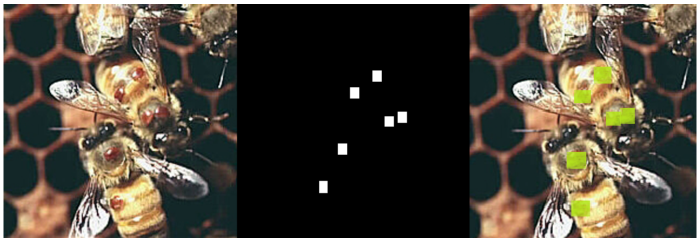

Fig. 8. Output pixel value in case of mite detection for training and Detection after training

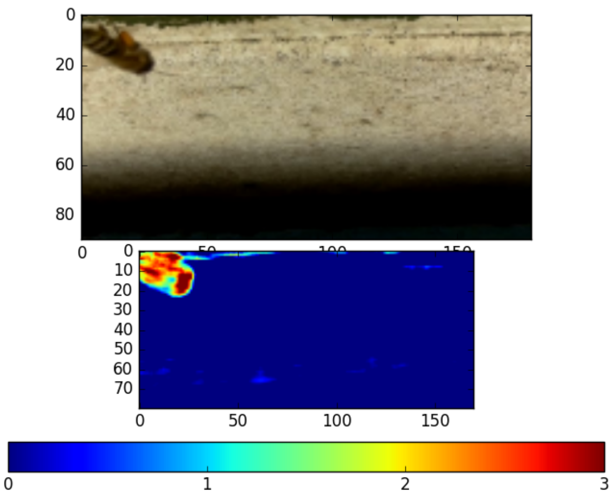

Fig. 9. Network applied to video frame to identify bees

(Figures 9 and 10) consisted in find bees within the frames. It is possible to see that the network identifies even the partially hidden bee in the Figure 10 .

In the second test, the network was trained to localize balls of pollen, which bees commonly carry in their legs after pollination. This test was performed in order to evaluate the efficiency of the network with small objects of interest, as in the future the objects this work aims to detect are small mites. In Figure 11, the red areas highlight the identified pollen on bees. Despite having good results with the collected videos, the results are not good enough for the overall purpose of this work. Some false detections happened in cases of high exposure variations. The image recognition method must be refined, to cope with these situations and to reach an accurate identification level in real time.

After this identification process, the algorithm can calculate the position of the detection and provide this information to the laser module so it can easily respond to this situation. In the next steps, this image recognition module must be able to differentiate wasps from bees and to recognize other enemies.

B. Laser Structure

Choosing the correct laser hardware is essential for the system to provide a good response time. The size of the insect

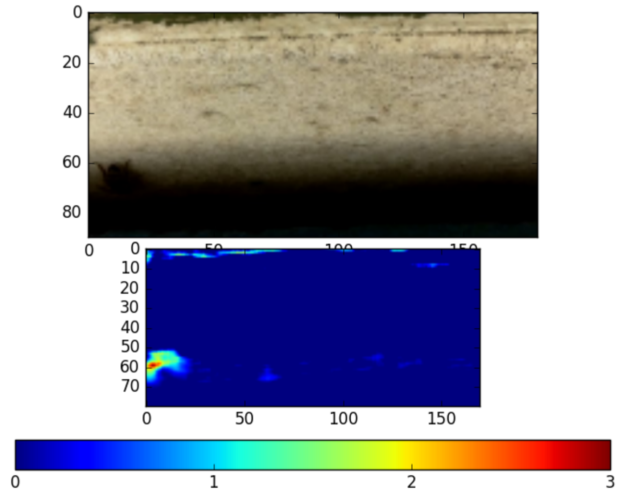

Fig. 10. Network applied to video frame to identify bees

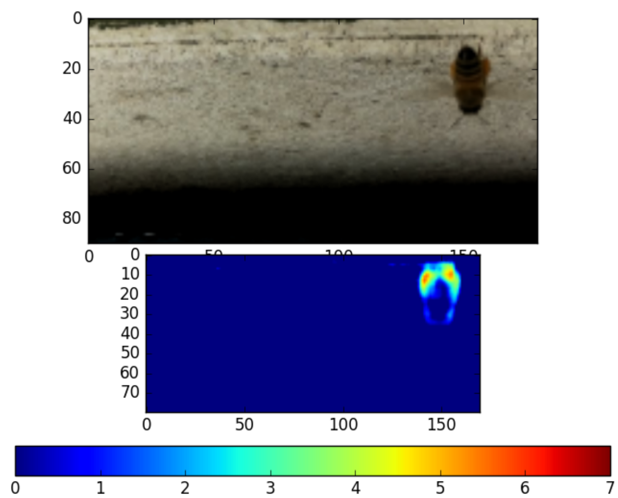

Fig. 11. Network applied to video frame to identify pollen

and its structure (e.g. amount of water in the body) must be considered so the system can apply the right amount of energy to kill it. It is important to consider that the movement of the insects/bees is, most of the times, fast, so it is important to have a laser powerful enough in a way that more energy can be applied in a shorter time. This way, it can successfully eliminate the different types of threats.

1W low-price laser diodes are well-suited and will be also tested in this work, since it has enough power to burn an undesired insect in a short time. At the moment, old dvd laser units (Figure 12) were tested as an alternative to support recycling, but the results showed up that it is not a suitable option, since these diodes have not enough power to execute

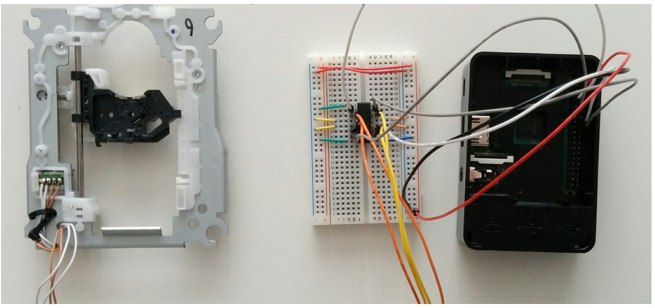

Fig. 12. DVD Laser Unit connected to the RaspPi

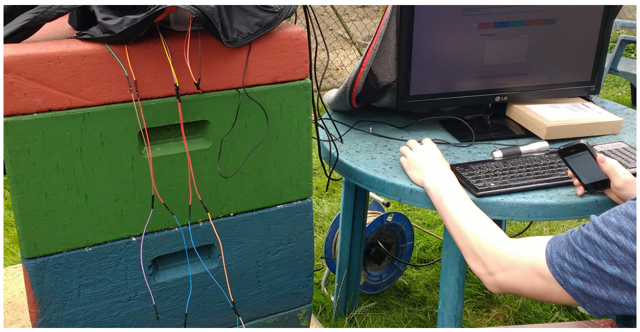

Fig. 13. In-field tests

the task at the desirable response-time.

Also, several tests are being conducted now so it can be possible to decide the best position for the laser and the camera, and measure the maximum response time after a detection. Different approaches, like stepper motors and mirrors, will be tested in order to decide the most appropriated one. These evaluations are truly important since the algorithm can be adjusted based on the performance the system had during the field tests (Figure 13). Also, it is possible to choose the best hardware options that suit well the objectives of this work.

C. Information System

As mentioned before in Section II, there are many Info Systems that monitor basic parameters via available sensors. However, one of the goals of this work is to use the open source HiveTool previously mentioned as a basis, to provide information that the beekeepers can access anywhere from their mobile phones. To make this possible, the Pi has a web server running as long as it has an internet connection.

This Information System gathers information such as temperature inside the hive, humidity, rain, weight of the hive, live sound and video images. Each one of this data is important to inform the beekeeper about the health of the colonies.

With weight information, it is possible to check if the bees are producing enough food to survive during the winter. This way, he can easily deduce if he should intervene in the process, introducing syrup to help the bees. Live sound can help the beekeeper to know if the bees are preparing to swarm, or if a new queen is born since a beekeeper can conclude on several stages of development of the bees by listening to sounds. Also, a notification can be sent to the user in case of sudden changes in the sound frequency.

Live video images can show the up-to-date situation of the beehive and the activity of the bees easily, enabling the beekeeper to take care of the colonies without the need of being there all the time.

V. Conclusion

This paper presented a system model to identify Varroa Mites in Honey Bees applying Image Processing techniques, and to eliminate them with a mechanical apparatus constructed to fire laser beams in case of mite detection. As a result of this study, we evaluated algorithms for the detection and localization of mites, as well as first insights on how precise and how fast a camera guided laser system has to be.

This first step, however, was necessary to demonstrate that the idea is possible and can bring interesting advantages if it is correctly applied. We are now working on putting the parts together and deploy a fully featured system in the real world, using our knowledge gather by the prototype studies presented here. The current version of this system is being now developed to run in portable devices such as Raspberry Pi 3, and to be capable of quickly detect and kill threats before they enter in the beehive.

This quick response is a challenge since the whole system has to be correctly integrated, with proper hardware and software solutions, to react without doing any collateral damages to the bees and without losing the target. With the final system, however, we expect to bring important advances in this field with a suitable and eco-friendly solution that can be easily adopted by beekeepers.

References

[1] J. Hayes Jr, R. M. Underwood, J. Pettis *et al.*, "A survey of honey bee colony losses in the us, fall 2007 to spring 2008," *PloS one*, vol. 3, no. 12, p. e4071, 2008.

[2] C. A. Mullin, M. Frazier, J. L. Frazier, S. Ashcraft, R. Simonds, J. S. Pettis *et al.*, "High levels of miticides and agrochemicals in north american apiaries: implications for honey bee health," *PLoS one*, vol. 5, no. 3, p. e9754, 2010.

[3] "HiveTool," http://hivetool.org/w/index.php?title=HiveTool.org, (Accessed on 08/09/2016).

[4] "Remote bee hive monitoring system," http://www.arnia.co.uk/, (Accessed on 08/09/2016).

[5] "Wi Hive - wireless beehive from bb7 and earthling," http://wihive.buzz/, (Accessed on 08/09/2016).

[6] "Home - solutionbee," http://solutionbee.com/, (Accessed on 08/09/2016).

[7] "EyesOnHives honey bee health monitor — keltronix," http://www.keltronixinc.com/, (Accessed on 08/09/2016).

[8] "Bee hive monitoring, bee keeping equipment - beewise," http://www.beewise.eu/, (Accessed on 08/09/2016).

[9] M. Giammarini, E. Concettoni, C. C. Zazzarini, N. Orlandini, M. Albanesi, and C. Cristalli, "BeeHive Lab project-sensorized hive for bee colonies life study," in *Intelligent Solutions in Embedded Systems (WISES), 2015 12th International Workshop on*. IEEE, 2015, pp. 121–126.

[10] F. E. Murphy, M. Magno, P. Whelan, and E. P. Vici, "b+WSN: Smart beehive for agriculture, environmental, and honey bee health monitoringpreliminary results and analysis," in *Sensors Applications Symposium (SAS), 2015 IEEE*. IEEE, 2015, pp. 1–6.

[11] F. E. Murphy, M. Magno, L. O'Leary, K. Troy, P. Whelan, and E. M. Popovici, "Big brother for bees (3B)energy neutral platform for remote monitoring of beehive imagery and sound," in *Advances in Sensors and Interfaces (IWASI), 2015 6th IEEE International Workshop on*. IEEE, 2015, pp. 106–111.

[12] M. Ramírez, J. P. Prendas, C. M. Travieso, R. Calderón, and O. Salas, "Detection of the mite varroa destructor in honey bee cells by video sequence processing," in *2012 IEEE 16th International Conference on Intelligent Engineering Systems (INES)*. IEEE, 2012, pp. 103–108.

[13] N. Hart and L. Huang, "Counting insects in flight using image processing techniques," in *Proceedings of the 27th Conference on Image and Vision Computing New Zealand*. ACM, 2012, pp. 274–278.

[14] "The hive project," http://hive.honeybeegardens.net/, (Accessed on 08/15/2016).

[15] W. Johnson, "Method and apparatus for laser pest control," Sep. 6 1994, uS Patent 5,343,652. [Online]. Available: https://www.google.com/patents/US5343652

[16] "Beela," http://www.beela.net/, 2015, (Accessed on 06/01/2016).

[17] "Laser bug zapper inches to market - ieee spectrum," http://spectrum.ieee.org/tech-talk/aerospace/military/laser-bug-zapper-inches-to-market-, (Accessed on 08/15/2016).

[18] M. D. Abràmoff, P. J. Magalhães, and S. J. Ram, "Image processing with ImageJ," *Biophotonics international*, vol. 11, no. 7, pp. 36–42, 2004.

[19] H. Richert, "Lokalisation von Schädlingen auf Bienen mittels Methoden der Bilderkennung," 2009.

[20] J. Hilgenberg, "Aufbau und Ansteuerung eines Aktuators zum Verfolgen eines Objekts auf einer zweidimensionalen Fläche," 2010.

[21] "Raspberry Pi 3 Model B - raspberry Pi," https://www.raspberrypi.org/products/raspberry-pi-3-model-b/, (Accessed on 08/14/2016).

[22] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, "Caffe: Convolutional architecture for fast feature embedding," in *Proceedings of the 22nd ACM international conference on Multimedia*. ACM, 2014, pp. 675–678.