Counting the Bumblebees Entering and Leaving a Beehive

Joaquín Salas* and Pablo Vera

Abstract

This paper describes a strategy for counting the bumblebees entering and leaving a beehive, where the order of the conditions of being at the doors or flying around them is what decides on one action or another. The former condition is detected with a Support Vector Machine (SVM) classifier, and the latter with a Bayesian tracker. We describe experiments to characterize the performance of the method proposed.

Figure 1. Beehive used in our research.

1 Introduction

It is estimated that by 2050 the world will have to produce 70% more food than now does [1]. Possibly due to factors such as the incentive of raising food prices, the reduction on water supplies, and an increase of soil erosion, intensive cultivation practices, such as the use of greenhouses, have been expanding[2], as well as the use of insect pollinators[3]. Therefore, there is a pressing need to build fast, reliable, economical and easy to deploy monitoring systems to assess the insects performance during the pollination process.

In this research, we aim to develop a bumblebee counting system for a portable beehive based on the use of computer vision techniques. We approach this as the problem of detecting within a tracklet the condition of a bumblebee being at the door or moving close to the door. In our model, when the former condition precedes the latter, we count a departure; while the contrary implies an arrival. We have developed a SVM classifier to detect bumblebees at the doors and we use a Bayesian tracker to follow the bumblebees activity outside the door. We explore previous work in §2; detail some of the techniques used in §3; and present results obtained with the model described in §4. Finally, we conclude summarizing this research and suggesting directions for future work.

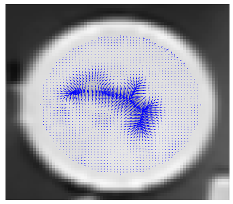
2 Related Work

The early detection of certain types of pests may lead to the prevention of crop damage in greenhouses. In [4], Martin and Moisan have presented a system which has the goal to detecting white flies and aphids. They apply a condition dependent, *e.g.*, sunny, cloudy, midday, or dusk, background model for detection. For insect classification and counting, they have translated expert knowledge into a dedicated language. Then, the insect behavior analysis is carried out with state diagrams where the transition is governed by events such as change in position or direction. Later, Bechar and Moisan [5] extended that work and developed an online pest counting algorithm. The feature they use to describe the insects is the ordered sequence of intensity values within their detected bounding box. Color images and Gabor features were later proposed by Kumar *et al.*[6] to train SVM classifiers.

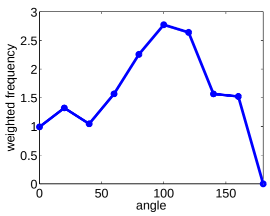
Using a different beehive than the one reported in this article, Campbell *et al.*[7] proposed a system to count the numbers of bees at the entrance of the beehive. They used a background model to detect bees and fitted an elliptical shape to the detected bees. In addition, they used motion models (including loitering, crawling, flying out, and flying in) to describe various

*The authors are with the Instituto Politecnico Nacional, Cerro Blanco 141, Colinas del Cimatario, Queretaro, Mexico, 76090. Joaquin Salas, `jsalasr@ipn.mx`, is the corresponding author. Thanks to Paul Riley for his comments to the manuscript. This research was partially supported by SIP-IPN through grant number 20121642.

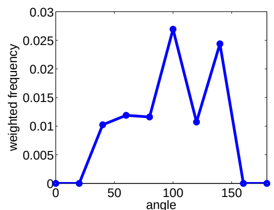
(a) A bumblebee at the tunnel.



(b) Gradient around the area of interest. The intensity image is shown in inverted gray scale.

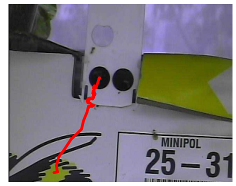


(c) Weighted HOG for (a).

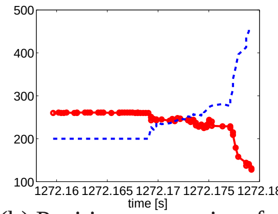


(d) Weighted HOG for an empty opening. Note the change of scale with respect to (c).

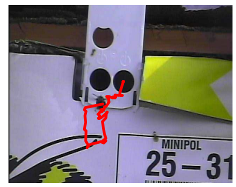
Figure 2. Bumblebee detection. The histogram of oriented gradient (HOG) is used to characterize the beehive doors and to detect bumblebees via a SVM classifier.



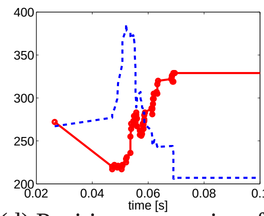
(a) Bumblebee departing.



(b) Position versus time for (a).



(c) Bumblebee arriving.



(d) Position versus time for (c).

Figure 3. Counting bumblebees. A departure will consists of a several detections at the door followed by a departing trajectory. Contrariwise, an arriving trajectory followed by detections at the door is considered an arrival. The dashed (blue line) and the continuous (red line) shows the vertical and horizontal position in pixels.

activities of the bees activities. Their tracking strategy consists on maximizing the sum of weighted edges in a bipartite graph. Other methods for counting bees include the use of capacitance-based sensors[8] and infrared sensors[9].

3 Approach Description

Our beehive is a 29[cm] wide, 21[cm] tall, and 26[cm] deep cardboard box (see Fig. 1). For our purposes, the salient features of the beehive are its two circular doors that are used by the bumblebees to enter or to leave. The beehive has a mechanism that prevents a bumblebee from entering through the exit or leaving through the entrance. Thus the beehive design simplifies the analysis of the bumblebees as it forces some behaviors. For example, a bumblebee that enters through the exit will invariably get out.

In our approach, we describe departure events as a set of observations $\mathscr{T}_d^i$, for $i = 1,\dots,m$, of the bumblebee at the door, followed by a departing trajectory $\mathscr{T}_o^i$, for $i = 1,\dots,n$. Contrariwise, an arrival event consists of an arriving trajectory $\mathscr{T}_o^i$, for $i = 1,\dots,p$, followed by a set of observations of the bumblebee at the door $\mathscr{T}_d^i$, for $i = 1,\dots,q$. In what follows, we describe how we monitor the beehive, detect bumblebees at the doors, and track them outside the beehive.

3.1 Beehive Registration

The beehive may be subject to motion due to wind, vibration, or occasional manipulation. To avoid disruption of the automatic analysis, it is convenient to dynamically monitor its position. The more important features of the beehive are its two openings that serve as the entrance and the exit for the beehive. For our beehive, these two openings have a circular and high contrast structure, which can be modeled by $(\bar{x}_k, \bar{y}_k, r_k)_{\mathscr{S}}$, where $(\bar{x}, \bar{y})$, and r are the center and radius of the circular structure, respectively, and $\mathscr{S}$ can be either `left` or `right` corresponding to a frontal image viewpoint.

To detect the circles, we use the implementation of the Hough transform developed by David Young *et al.*[10]. Afterwards, the positions of the two doors $(\bar{x}_{k+1}, \bar{y}_{k+1}, r_{k+1})_{\mathscr{S}} \leftarrow (\bar{x}_k, \bar{y}_k, r_k)_{\mathscr{S}} + (\Delta\bar{x}_k, \Delta\bar{y}_k, \Delta r_k)_{\mathscr{S}}$ are updated using robust estimation with a Kalman filter[11].

3.2 Bumblebee Detection

There are two distinct situations in which a bumblebee needs to be detected: one is when it is at either of the beehive doors and the other is when it is close to the doors.

The area corresponding to the doors is mostly dark. It is only when a bumblebee shows up that some contrast appears. Under these conditions, it very difficult to perform a detailed bumblebee body analysis. In our approach, we are satisfied with a yes or no answer to the question of whether there is a bumblebee visible at the door. Therefore, we train a SVM [12] using a descriptor based on the weighted value of the histogram of oriented gradient (HOG) as follow.

Let $\mathscr{R} \leftarrow (\overline{x}, \overline{y}, r)$ be the current descriptor for the geometry of a door opening. The gradient on that area $\nabla I_{\mathscr{R}} = (\theta_{\mathscr{R}}, M_{\mathscr{R}})$ is composed of vectors with an orientation $\theta_{\mathscr{R}}$ and a magnitude $M_{\mathscr{R}}$. A 9-bins weighted histogram $\mathbf{z} = h(\theta_{\mathscr{R}}, M_{\mathscr{R}})$ is constructed. The corresponding weight is directly related to the magnitude of the gradient at the position of a certain orientation. During training, a set of a positive $\{\mathbf{z}_k^P\}$ and b negative $\{\mathbf{z}_k^N\}$ samples are used to train a SVM classifier. Then, during operation, a similarly computed HOG-feature is given to the classifier to determine if a bumblebee is (yes) or is not (no) at the door.

To detect the bumblebees flying around the doors, we use a layered background model [13] to detect the foreground pixels that correspond to moving objects.

3.3 Tracklet Construction

It is frequently difficult to track bumblebees because of their relatively high flying speed, which equals a large displacement, in pixel terms, from frame to frame. Nonetheless, for our application, the important tracks are the ones occurring close to the doors, where we must distinguish between a trajectory is heading toward the door or is heading the opposite direction.

In [14], Javed *et al.* defined a Bayesian inference framework to track objects across disjoint views. In what follow, we apply that paradigm to the construction of bumblebee tracklets. Let $\{O_{j,1}, \ldots, O_{j,m_j}\}$ be the set of observations made at frame j, where each $O_{j,b}$ corresponds to a particular bumblebee. In our case, each observation $O_{j,b}$ includes its location at a given moment during its trajectory $O_{j,b}(\mathrm{st})$.

Similarly to Javed *et al.*[14], let $k_{j,b}^{j+1,d}$ define the hypothesis that $O_{j,b}$ and $O_{j+1,d}$ corresponds to the same bumblebee. A tracklet is formed when we find the set of correspondences $K = \{k_{j,b}^{j+1,d}\}$ such that $k_{j,b}^{j+1,d} \in K$ if - and only if - $O_{j,b}$ and $O_{j+1,d}$ corresponds to the same bumblebee. Assuming independence between observations, the following expression holds

$$P(K \mid O) = \prod_{k_{j,b}^{j+1,d} \in K} P_{j,j+1}\left(k_{j,b}^{j+1,d} \mid O_{j,b}, O_{j+1,d}\right),$$

which expresses the conditional probability of a certain correspondence $k_{j,b}^{j+1,d}$, given the observations $O_{j,b}$, and $O_{j+1,d}$. From Bayes theorem, it follows that

$$\begin{aligned} &P_{j,j+1}\left(k_{j,b}^{j+1,d} \mid O_{j,b}, O_{j+1,d}\right) \\ &= \frac{P_{j,j+1}\left(O_{j,b}, O_{j+1,d} \mid k_{j,b}^{j+1,d}\right) P_{j,j+1}\left(k_{j,b}^{j+1,d}\right)}{P_{j,j+1}\left(O_{j,b}, O_{j+1,d}\right)}. \end{aligned} \tag{1}$$

Using the above equation, the expression to maximize corresponds to

$$\begin{aligned} &P_{j,j+1}\left(O_{j,b}, O_{j+1,d} \mid k_{j,b}^{j+1,d}\right) \\ &\quad = P_{j,j+1}\left(O_{j,b}(\mathrm{st}), O_{j+1,d}(\mathrm{st}) \mid k_{j,b}^{j+1,d}\right) \\ &\quad = e^{-\|\mathbf{x}_j - \mathbf{x}_{j+1}\|/\alpha}, \end{aligned} \tag{2}$$

where $\mathbf{x}_j$ is the bumblebee position at frame j and α is an empirical constant. The solution corresponds to the hypothesis K' in the solution space Σ that maximizes

$$K' = \arg\max_{K \in \Sigma} P(K \mid O). \tag{3}$$

The trajectory is the result of combining iteratively the associated observations with the use of a Kalman filter[11]. An illustration of a tracklet is presented in Fig. 3.

3.4 Counting Bumblebees

A tracklet $\mathscr{T}$ is defined over a period of time (t_i, t_f). Furthermore, we distinguish two types of tracklets, those at the doors $\mathscr{T}_d$, extracted using the SVM detector, and those in the area around $\mathscr{T}_o$, result of the Bayesian tracker. For every tracklet at the door $\mathscr{T}_d = (t_i^d, t_f^d)$, we verify if there is a tracklet $\mathscr{T}_o = (t_i^o, t_f^o)$ during the same period of time. That is, we check whether the condition $(t_f^d > t_i^o) \wedge (t_f^o > t_i^f)$ holds true. For a bumblebee detected at anyone of the doors, we do not really know with certainty where it is located within the door's opening. Therefore, we define an area of influence around the door as the points $\mathbf{x} = (x, y)$ inside the circle $(x - \overline{x})^2 + (y - \overline{y})^2 \leq r^2$.

To count the number of bumblebees entering and leaving, we combine the $\mathscr{T}_d$ and $\mathscr{T}_o$ tracklets whenever there is time and space overlap for the end points of $\mathscr{T}_o$, to create tracklet $\mathscr{T}_f$. Then, an arrival is added whenever the first point of the tracklet is outside a door's area and the endpoint is inside the door's area. On the other hand, a departure is detected when, for the tracklet $\mathscr{T}_f$, the first point is within the door's area and the final point is outside that area. All other tracklets are discarded.

4 Experimental Results

To test the method just described, we captured a sequence of 326,000 color images at a resolution of 640 columns and 480 rows, in about three hours. The sequence was captured and stored on a hard disk while all the processing is completed offline using MATLAB programs.

To train the SVM classifier, we used 950 positive and 1048 negative samples. After testing with 400 additional images, we obtained a true positive rate of 99.16% and a false positive rate of 0.56%.

During the sequence, there were 65,470 images with 92,142 bumblebee detections. We eliminated tracklets with fewer than 4 observations, which left 8,041 statistically probable tracklets. After combining the trajectories and filtering out the tracklets that did not meet the space-time overlapping conditions detailed in §3.4, 95 tracklets remained. To compare the output of the system with ground truth, we reviewed manually the tracklets occurring in the sequence and compared these with the ones being detected. The number of bumblebees arriving was 55 (versus 55 actually arriving), and departing was 35 (versus 52 actually departing). There were 14 tracklets that departed and arrived at the same door (versus 20 in the sequence). And there were 9 tracklets that departed from one door and arrived at the other one (versus 11 in the sequence).

Conclusion

In this article, we present a system to count the number of bumblebees entering and leaving a beehive. We have shown that the beehive used in this work leads to a particularly suitable computer vision system, in which the problem is reduced to the construction and interpretation of a tracklet. The construction of the tracklet is based on the combined use of a SVM classifier for the bumblebees at either of two door, complemented with a Bayesian tracker for the bumblebees flying around the doors. The overall performance of the counting system is satisfactory.

In the future, we are planning to extend our observations for longer periods of time, incorporating data about ambient temperature, humidity, and brightness, such that an entrance and departure rate may be assessed as normal or abnormal. Also, it may be useful to implement the algorithms in a mobile platform, which will provide a portable and flexible beehive monitoring system.

References

[1] Food and A. O. of the United Nations, "How to Feed the World in 2050," Tech. Rep., 2009.

[2] INEGI, *7mo Censo Agropecuario y Forestal*, 2007.

[3] H. Velthuis and A. van Doorn, "A Century of Advances in Bumblebee Domestication and the Economic and Environmental Aspects of its Commercialization for Pollination," *Apidologie*, vol. 37, no. 4, pp. 421–451, 2006.

[4] V. Martin and S. Moisan, "Early Pest Detection in Greenhouses," in *VAIB*, 2008.

[5] I. Bechar and S. Moisan, "On-line Counting of Pests in a Greenhouse using Computer Vision," in *VAIB*, 2010.

[6] R. Kumar, V. Martin, and S. Moisan, "Robust Insect Classification Applied to Real Time Greenhouse Infestation Monitoring," in *VAIB*, 2010.

[7] J. Campbell, L. Mummert, and R. Sukthankar, "Video Monitoring of Honey Bee Colonies at the Hive Entrance," in *VAIB*, 2008.

[8] J. Campbell, D. Dahn, and D. Ryan, "Capacitance-based Sensor for Monitoring Bees Passing through a Tunnel," *Measurement Science and Technology*, vol. 16, p. 2503, 2005.

[9] M. Struye, H. Mortier, G. Arnold, C. Miniggio, and R. Borneck, "Microprocessor-controlled monitoring of honeybee flight activity at the hive entrance," *Apidologie*, vol. 25, no. 4, pp. 384–395, 1994.

[10] D. Young, H. Tunley, R. Samuels, and U. of Sussex. School of Social Sciences. Cognitive Studies Programme, *Specialised Hough Transform and Active Contour Methods for Real-time Eye Tracking*. University of Sussex, Cognitive & Computing Science, 1995.

[11] R. E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," *Journal of Basic Engineering*, vol. 82, no. 1, pp. 35–45, 1960.

[12] N. Cristianini and J. Shawe-Taylor, *An introduction to Support Vector Machines and other Kernel-based Learning Methods*. Cambridge Univ Pr, 2000.

[13] P. Kelly, Ó. Conaire, D. Monaghan, J. Kuklyte, D. Connaghan, P. Agapito, J. Diego, and P. Daras, "Performance Analysis and Visualisation in Tennis using a Low-cost Camera Network," 2010. [Online]. Available: http://doras.dcu.ie/15736/

[14] O. Javed, K. Shafique, Z. Rasheed, and M. Shah, "Modeling Inter-Camera Space-Time and Appearance Relationships for Tracking Across Non-Overlapping Views," *Computer Vision and Image Understanding*, vol. 109, no. 2, pp. 146–162, 2008.