Video Monitoring of Honey Bee Colonies at the Hive Entrance

Jason Campbell, Lily Mummert, Rahul Sukthankar
{jason.d.campbell,lily.b.mummert,rahul.sukthankar}@intel.com
Intel Research Pittsburgh

Abstract

The flight activity of a honey bee colony is an important indicator of its strength and condition. We propose the use of video sensing to monitor arrivals and departures at the hive entrance. We describe the challenges of tracking and counting bees visually in the uncontrolled outdoor environment of an apiary, and detail a hardware platform and software algorithms we have developed to meet many of those challenges. Finally, we discuss our preparations for rigorously evaluating the proposed monitoring system and describe early results.

1. Introduction

Honey bees have been a focus of recent attention because of their vital role in pollinating agricultural crops, and because of long term and recent precipitous declines in the number of colonies [6]. Beekeepers assess colony health by manually inspecting hives, beginning with visual observation of flight activity. A rough estimate of traffic, along with knowledge of local conditions and prior behavior, can indicate if closer inspection or intervention is warranted.

Attempts to automate activity monitoring at the hive entrance date back nearly a century [11]. Early methods are reviewed in Pham-Delégue *et al.* [12]. Today, commercially-available activity counters are based on infrared sensing [10, 14]. A device is placed in the hive entrance that consists of up to 32 bidirectional, bee-sized tunnels, each equipped with a dual photoreceptor to determine direction of movement. Drawbacks of this approach include obstruction of bee movement and spurious counts caused by debris in the tunnels, which must be cleaned regularly. More recent work on a capacitance-based sensor to monitor bumblebees passing through a tunnel addresses some of these drawbacks [2]. Counting systems have been developed for tracking specific bees using techniques such as metal detection [9] and bar code scanning [3, 13]. These methods require manipulation of individual bees, and are thus infeasible in a practical setting.

Figure 1. Instrumented bee hive

Flight activity is affected by many factors both internal and external to a colony, such as population, presence of an egg-laying queen, weather conditions, availability of nectar and pollen, disease, and exposure to toxins. Despite this complexity, activity counters provide useful practical information. For example, they reveal phenomena such as swarming, an event of importance to beekeepers that is brief and difficult to predict, but is marked by large numbers of bees leaving the hive. Other events that cause significant changes in short-term activity include thunderstorms and exposure to pesticides. Bromenshenk *et al.* found two measures derived from activity counts most useful: net losses, and the coefficient of variation for activity between hives at the same site [1]. Spikes in activity, large losses, unsustainable loss rates over time, less active colonies relative to their peers, and colonies whose behavior deviates substantially from their established norms would all merit investigation by the beekeeper.

The use of video for monitoring bees is relatively recent, now feasible because of the availability of commodity digital cameras and high-performance computing devices. Several studies have aimed at assisting behavioral analysis of activity inside the hive, such as bee dance communication [16], by automatically tracking bees [7, 8] and labeling their behaviors [5, 15]. Outside the hive, video has been used to track flying bees in an orchard to study pollination [4].

In this paper, we propose the use of video for activity monitoring at the hive entrance in a practical setting. To our knowledge, this is the first use of video for this purpose. The main advantage of video is that it does not interfere with normal colony activity, though accurate interpretation of the video stream poses a number of challenges. In the rest of this paper, we describe our sensing platform, and discuss techniques to detect, track, and count arriving and departing bees. Our goal is to measure hive interaction with the outside world in a way that enables beekeepers to focus their attention where it is needed.

2. Sensing Platform

Our approach monitors flights to and from the a bee colony using a camera positioned over the unmodified entrance of a standard hive, as shown in Figure 1. We chose a downward-facing view in order to maximize the benefit of the white background offered by the landing platform just outside the hive entrance, and to minimize the scale and perspective differences that would be caused by larger distances.

We use a Unibrain Fire-i™ digital board camera equipped with a wide angle lens ($f = 2.1mm, 80°$ horizontal view angle). This wide angle view covers the entire 40cm (16 in) width of the entrance platform while mounting the camera only 20cm (8 in) above that platform. Thus the camera can be attached within the height of a single primary hive body itself rather than relying on the presence of at least one expansion box ("super" in apiarist terminology). We can hence monitor hives from the very earliest stages.

The camera itself is mounted within a plastic weather shield custom fabricated using fused-deposition modeling (see Fig. 2, dimensions are in centimeters). A port on the side of the enclosure permits access for an IEEE 1394 bus cable and, optionally, for a power cable. The enclosure is attached to the hive with removable adhesive strips.

The camera acquires color 640x480 video frames at 30 frames/sec. We have gathered video data from two different hives, the first established from a 3-pound package in April 2007, and the second established with four frames of brood from two existing colonies in May 2008. Sample video frames from the second hive, taken in July 2008, are shown in Figure 3.

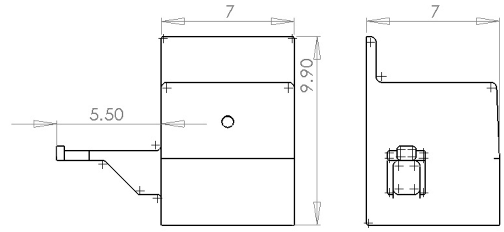

Figure 2. Camera enclosure

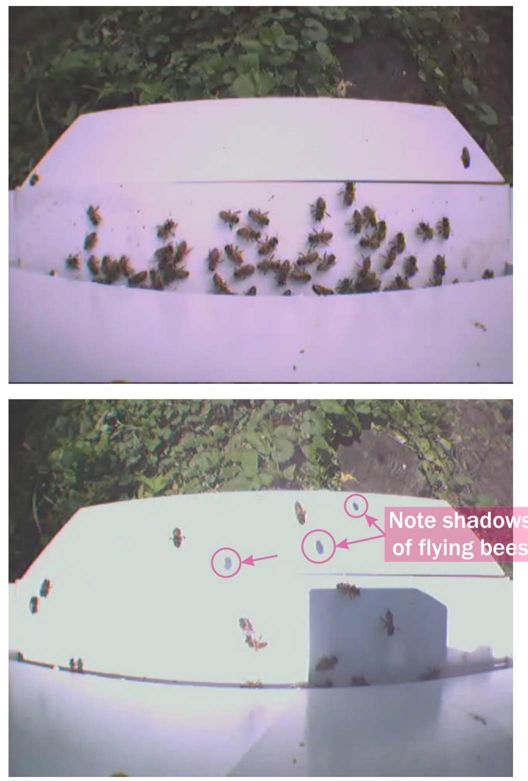

Figure 3. Sample video frames

3. Measuring Activity

Measuring flight activity at the hive entrance from video involves detecting bees and tracking their motion through a sequence of frames.

3.1 Challenges

There are several reasons why bee detection and tracking is a difficult computer vision problem.

First, as seen in Figure 3, in a typical image acquired from the hive-mounted camera a single bee occupies only a very small portion of the image (approximately 6×14 pixels). Bee detection might be easier with higher-resolution cameras or with multiple cameras each placed closer to the hive entrance, but only at a substantial increase in cost as well as physical and computational complexity, limiting utility in practical settings.

Second, because bee hives are outdoors, lighting conditions can vary significantly with the time of day, season and weather. Shadows are cast by the camera enclosure, moving bees, and moving foliage overhead. These all hinder naive approaches to background subtraction. Although it is possible to arrange clear lighting in the hive entry area this demands onerous hive-placement constraints vis-a-vis trees, buildings, and compass points. Artificial lighting, such as routinely used in industrial machine vision, would be difficult to place in the field and could affect bee behavior.

Third, even at 30 frames/second, flying bees can cover a significant distance between frames. This movement complicates frame-to-frame matching as worker bees from a hive are virtually identical in appearance. Furthermore, bees transition quickly between loitering, crawling, and flying modes of movement and change directions unpredictably; this makes it impossible to track them using one unimodal motion model.

Fourth and finally, the scene is often cluttered. Bees can group or occlude each other in ways that challenge simple segmentation and tracking approaches. This problem has also been observed for video taken inside the hive [7, 5, 15].

3.2 Detection

Our current bee detector performs adaptive background subtraction using a background model derived from a running average of the most recent 300 video frames. We then match an elliptical, graduated template at 16 orientations across each background-subtracted video frame. We presently consider only one size template. Adding sizes would be a straightforward extension. The graduated template encourages centering of the detection region on each bee and penalizes oval objects which do not exhibit bees' characteristic round appearance in depth as well as outline.

3.3 Motion Models

The amount a bee moves between frames depends on its behavior. We distinguish between four different behaviors: *loitering*, *crawling*, *flying out* and *flying in*. These have significantly different characteristics. For example, crawling bees typically do not move significantly between frames, while flying bees do. Bees flying towards the hive entrance hover while looking for a place to land, so their motion is more lateral than longitudinal. Bees flying away from the hive entrance tend to exhibit the greatest forward motion per frame.

We model frame-to-frame changes in bee position and orientation using Gaussian distributions for crawling and flying. These models are derived from manual motion analysis of a small number of video frames. Orientation changes are modeled separately from position. Loitering is detected with a small distance threshold.

3.4 Tracking

We treat the task of tracking bees from frame-to-frame as an assignment problem, and solve it using maximum weighted bipartite graph matching. Specifically, each detection in frame i is associated with a node in the first set, $\mathcal{A}$ and each detection in frame $i+1$ with a node in the second set, $\mathcal{B}$. The weighted edge between a pair of nodes $a \in \mathcal{A}$ and $b \in \mathcal{B}$ is proportional to the likelihood that a bee with pose a could move to pose b in the span of a single frame.

Bee motion is expressed by the four motion models described in Section 3.3. We make the simplifying assumption that a bee can change its mode of motion instantly among these modes on a frame-by-frame basis, and that all of them are equally likely *a priori*.[1]

We define the weight on each edge of the graph using the most likely motion model for the given hypothesis. In general, this means that pairs of detections spaced far apart acquire a weight from one of the flying models, those within a pixel or two are associated with loitering, and the remainder are explained by crawling. Because bees in one frame may not appear in the next (entering the hive or flying out of the frame), and new bees may appear (exiting the hive or flying into the frame), we augment the graph with dummy nodes and edges for these hypotheses. Departures and arrivals are determined by examining the tracks of unmatched bees. Because it is possible to lose track of a bee temporarily (e.g., occlusions), inconclusive tracks are retained for a few frames in case they can be reestablished.

4. Bee Activity Data

We have created a manually-annotated dataset of bee video to train motion models (Section 3.3) and to evaluate the overall system. The training dataset for the motion models consists of 600 frames annotated with the motion type and frame-to-frame change in position and

[1] We plan to refine the models and transitions as additional empirical data on bee motion is collected.

orientation for every visible bee. We have annotated an additional 1800 frames with ground truth of arrivals, departures and number of visible bees in each frame.

We plan to annotate additional video from an established colony to improve the motion models and provide a more rigorous basis for evaluation. Because the surfaces of this hive are more weathered and dirty, and because the colony is larger and more active it represents a more complicated test case.

5. Preliminary Results

One of our goals was to not substantially alter the bees' environment, and so far impact on hive activity appears to be minimal. In particular, the bees exhibit no particular interest in the camera or housing (except for understandable interest during installation).

We implemented the system described in Section 3 and are testing it on the annotated dataset described in Section 4. Our initial experience is that the counter has basic functionality, and is resilient to errors such as track loss and switching between objects as long as direction can be discerned.

The counter detects bees with precision 0.94 and recall 0.79 on the annotated dataset. False negatives occur largely at the edges of the frame, where wide angle lens distortions are severe. False positives occur when bees fly towards the camera and appear larger than usual, generating multiple detections. Using multiple size templates for detection or an appearance model trained on bee images from the dataset should improve detection in these cases.

The counter overcounted arrivals by 2% and undercounted departures by 7% on the annotated data set. Undercounting is caused by false negatives in the detector compounded by track aliasing, in which the track of an arriving bee is incorrectly associated with that of a nearby departing bee, and vice versa. Incorporating more detailed models of bee orientation into the motion model and scoring entire tracks based upon structure should address this problem.

The most important bit of orientation information — whether a bee is facing towards or away from the hive opening — is also the most challenging bit of information to obtain. Preliminary analyses of pixel data suggests it will be possible to distinguish, for instance, heads from abdomens directly using a more sophisticated appearance model.

6. Conclusion

This paper presents a video-based approach for measuring flight activity of honey bee colonies. The primary contribution is a non-invasive system that can be deployed in an apiary with minimal disruption. Preliminary results indicate that our methods for adaptive background subtraction, template-based bee detection and tracking show promise under real-world conditions.

References

[1] J. J. Bromenshenk, G. C. Smith, B. E. King, R. A. Seccomb, G. Alnasser, C. B. Henderson, M. R. Loeser, and C. L. Wrobel. New and Improved Methods for Monitoring Air Quality and the Terrestrial Environment. Technical Report ADA326262, National Technical Information Service, Springfield, VA, November 1996.

[2] J. M. Campbell, D. C. Dahn, and D. A. J. Ryan. Capacitance-based sensor for monitoring bees passing through a tunnel. *Measurement Science and Technology*, 16, November 2005.

[3] Data2 Corporation. Data2 Creates World's Smallest Barcode. Press release, `http://www.data2.biz/success/content/ag-content.html`.

[4] V. Estivill-Castro, D. C. Lattin, F. Suraweera, and V. Vithanage. Tracking bees — a 3D, outdoor small object environment. In *Proceedings International Conference on Image Processing*, 2003.

[5] A. Feldman and T. Balch. Representing honey bee behavior for recognition using human trainable models. *Adaptive Behavior*, 12(3–4), 2004.

[6] J. K. Kaplan. Colony Collapse Disorder: A Complex Buzz. *Agricultural Research*, May–June 2008.

[7] Z. Khan, T. Balch, and F. Dellaert. A Rao-Blackwellized Particle Filter for EigenTracking. In *Proc. Computer Vision and Pattern Recognition*, 2004.

[8] T. Landgraf and R. Rojas. Tracking honey bee dances from sparse flow optical fields. Technical Report B 07-11, Freie Universität Berlin, Inst. für Informatik, 2007.

[9] L'Institut national de la recherche agronomique (INRA). Tracking bees to study their behavior. Press release, `http://www.international.inra.fr/press/tracking_bees`, June 2006.

[10] Lowland Electronics bvba. BeeSCAN Instruction Manual. `http://users.pandora.be/lowland`.

[11] A. E. Lundie. The flight activities of the honey bee. United States Department of Agriculture Bulletin No. 1328, 1925.

[12] M.-H. Pham-Delégue, A. Decourtye, L. Kaiser, and J. Devillers. Behavioral methods to assess the effects of pesticides on honey bees. *Apidologie*, 33:425–432, 2002.

[13] M. T. Sanford. Bar Codes on Bees and Honey. *APIS: Apicultural Information and Issues*, 7(5), 1989.

[14] M. H. Struye, H. J. Mortier, G. Arnold, C. Miniggio, and R. Bornek. Microprocessor-controlled monitoring of honeybee flight activity at the hive entrance. *Apidologie*, 25:384–395, 1994.

[15] A. Veeraraghavan, R. Chellappa, and M. Srinivasan. Shape and Behavior Encoded Tracking of Bee Dances. *IEEE Transactions on PAMI*, 30(3), 2008.

[16] K. von Frisch. *The Dance Language and Orientation of Bees*. Harvard University Press, 1967.