Bee Hive Traffic Monitoring by Tracking Bee Flight Paths

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Abstract: The number of pollinator insect is in decline in Europe and this raises concerns about the supply of pollination services to agriculture. Thus, countries with a low number of honeybees are more vulnerable to negative shifts in wild pollinator communities. Consequently, the demand for honeybee pollination is higher than ever but beekeepers are also very concerned by the strength of their colonies. To measure this factor, a very important indicator to take into account is the flight activity at the beehive entrance. A quantitative measure of the activity can be related to the environment and does not only benefit beekeepers but scientists too. In this paper, we present a complete method of measuring this activity. It is represented by the number of bees going in or out of the beehive. The developed method is divided in three parts: the first one consists in bee detection thanks to several image transformations using background subtraction and ellipse approximations. The second one is about tracking bees, by assuming their future positions in order to determine whether they are going in or getting out of the beehive. The last one consists in counting the bees. Finally, the experimental results demonstrate that our system created with limited resources can be used to precisely measure the flight activity at the beehive entrance.

1 INTRODUCTION

Today, beekeepers are experiencing numerous losses of colonies during flowering periods or when phytosanitary products are applied, mainly due to the effects of pesticides. While honey production is the primary economic contribution of bee farms, pollination by bees is of much greater economic and environmental importance. Yet in most cases it is a side effect which is not taken into consideration by the beekeepers nor recognized by public authorities. Unfortunately, the effects of pesticides are also combined with the effects of predators (Asian Hornets), parasites (Varroa Destructor), viruses often propagated by these parasites and bacterial diseases to endanger the honey bee (Apis Mellifera) (Vidau et al., 2011). We have now entered a critical era for biodiversity and many authors believe that the honey bee is an essential indicator of these environmental issues (Potts et al., 2010). Beekeepers are important stakeholders who can contribute to the conservation of the species. Some have set up devices for observing their colonies to better monitor them for reasons linked to profitability but also for naturalistic observations. Technology can help beekeepers save and protect their bees, and scientists are studying the bees behavior by the mean of EBM (Electronic Beehive Monitoring) (Lebwohl, 2009). Its purpose is to collect critical information/data on the behavior and phenology of a colony without invasive beehive inspection and without disturbing bees in their daily tasks. The IOT (Internet Of Things (Atzori et al., 2010)) ecosystem provides the beekeeper with the material means for such observations, giving rise to connected beekeeping. This new discipline assists beekeepers in helping their bees and allows them to observe their hives remotely. The connected beehive is equipped with numerous sensors and can be used to measure the weight, temperature, relative humidity, traffic intensity, and many other parameters. These data are sent by the means of a GSM or a 6LoWPAN network to the beekeeper's personal dashboard (Kushalnagar et al., 2007). From a computer or a smartphone, the beekeeper's account can be used to monitor the bees, including their productivity and health. Beekeepers receive alerts by e-mails or by phone (texts) when their intervention is necessary (theft, honey flow, swarming...), which saves time and eliminates unnecessary visits to the hive. The connected beehive is also a tool for learning and communication. By means of its dashboard, non-professional beekeepers receive alerts and large companies can share their

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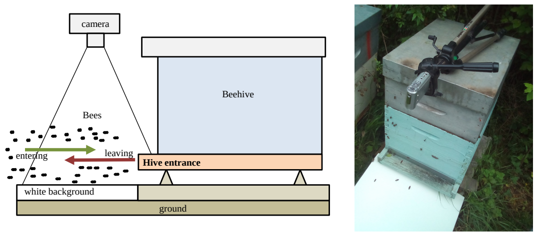
commitment to protecting bees.

The monitoring of bee traffic gives the beekeeper an accurate indication of the strength of the colony. Bees which leave and enter the hive collect nectar as well as pollen and water. The intensity of the comings and goings shows the number of foragers in the hive and how active the hive is. Indeed, flight activity is a key factor of colony strength, health and organizational structure. In addition, as part of a procedure for assessing losses of bees due to phytosanitary products, it is interesting to count the outgoing as well as the incoming bees so as to evaluate the loss of foragers at the end of the day. Computer vision can achieve these tasks accurately and this paper paper presents a new method for measuring the activity of bee at hive entrance.

2 RELATED WORK

Quantifying human impact on biodiversity in order to alert humanity or propose solutions is an important line of research for ecology and other disciplines. Acoustic signals (Diep et al., 2016) or video using deep learning (Villon et al., 2016) are useful to observe and study activities of some animal species. In this context, the issue of bee behavior has been dealt with by many authors using computer vision. Feldman and Balch study bee movements inside the hive, especially for waggle dance detection (Feldman and Balch, 2004). The authors of (Khan et al., 2004) use a particle filter to follow crawling bees inside the hive. Meanwhile, a method is preposed in (Kulyukin, 2017) to count bees on the landing pad of the hive, by computing 1D Harr wavelet spikes. Campbell et al. also propose the use of video sensing to monitor arrivals and departures at the hive entrance by using elliptical templates to detect insects followed by a graph matching in the tracking step (Campbell et al., 2008). At that time, they faced difficulties linked to resolution using a 640×480 video, which implies that bees were approximately represented as 6×14 pixels. A stereo vision-based system is presented in (Chiron et al., 2013). They use a detect-before-track approach that employs two methods: hybrid segmentation using both intensity and depth images, and tuned 3D multi-target tracking based on the Kalman filter and Global Nearest Neighbor. A tracking algorithm based on Viola-Jones approach (Viola and Jones, 2001) is developed in (Miranda et al., 2012) to help assess the quantity and variety of pollinators in a given environment in the determination of the relationship between flowers and pollinators. However, the multi-detection process results in track fragmentations and makes it



(a) Sketch of the device (b) Real hive

Figure 1: Diagram of the bee path drawing.

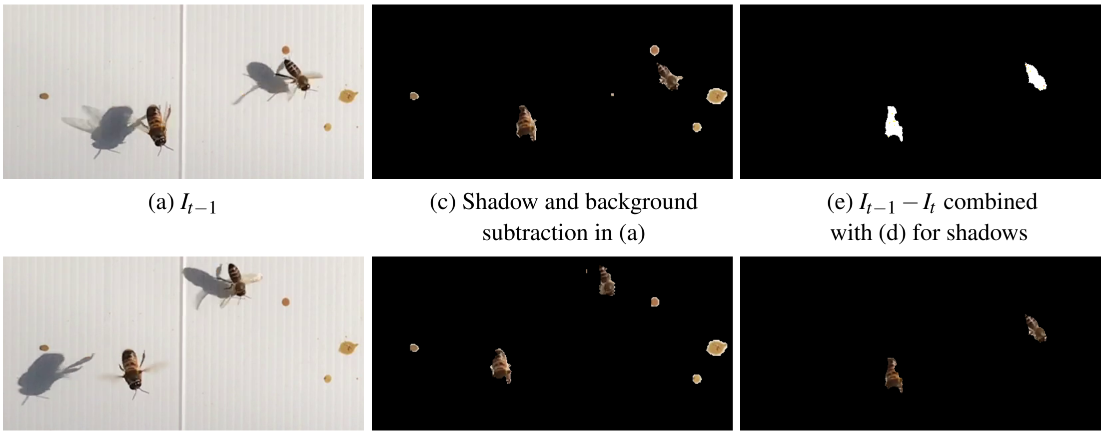
difficult to analysis the trajectories of several objects (Prokaj et al., 2011). Moreover, in aerial videos bees can have random movements, contrary to cars, which have generally rectilinear trajectories (Perera et al., 2006). Babic et al. (Babic et al., 2016) propose a method on embedded implemented systems co-located with a hive in order to detect bee that have pollen. The classification is performed using color variance and a nearest mean classifier. The Signal-to-Noise Ratio (SNR) between a reference image and a current image is utilized in (Tashakkori and Ghadiri, 2015) to estimate the number of bees at the entrance of a hive. This method is not precise if bees are at different elevations, moreover, it requires an a-priori information about the pixel number for the representation of the bees in the image. Histogram of Oriented Gradients (HOG) features is used in (Azarcoya-Cabiedes et al., 2014) to detect the presence of bumblebees, but changes in lighting and insect shadows affect de detection. Nevertheless, authors suggest the performance can be improved by using a detection-and-tracking strategy. Contrary to our approach, the segmentation is performed on crawling bees, as this is the case the algorithm developed in (Tu et al., 2016). The authors use a background subtraction method to segment the images and count the number of segmented pixels in a grayscale image in order to evaluate the number of bees entering in the hive.

3 DETECTION AND TRACKING

3.1 Technical Challenge

The technical challenge is to measure the in-and-out activity at a beehive entrance without sophisticated devices and with the smallest amount of resources. The device we propose is described in Fig. 1. Only the 4 following items are involved in the core issues of this paper:

- a camera
- a white background



(a) I_{t-1} (c) Shadow and background subtraction in (a) (e) $I_{t-1} - I_t$ combined with (d) for shadows

(b) I_t (d) Shadow and background subtraction in (b) (f) image in (e) with with original colors

Figure 2: Example of segmentations for Algo 4: two bees are detected. Edges are extracted on binary images as image in (e) to approximate ellipses.

- a hive with bee traffic
- image processing bee counting software.

A camera records the bee traffic which is enhanced thanks to a white background and an algorithm that computes the activities of the hive (arrivals and departures). The camera is placed above a Dadant beehive entrance, being sure that the entire entrance width is covered by the camera. The 12 megapixels camera sensor is equipped with a wide-angle lens (28mm, f/1.8). It acquires 1080p videos at 60 frames per second (fps). Videos are saved in the MOV format and resized for different experiment evaluations: 1080p, 720p, 540p and 360p at 60 fps or 30 fps. Finally, when bees fly close to the white background, Table 1 presents their approximate length in pixels for our experiments.

3.2 Problem of Shadows and Bee Detection

The daily activity of the bees starts at sunrise and stops at sunset. The phases of high activity often match with very sunny periods and this periods is fundamental for evaluating the hive health. Nevertheless, as the camera is placed verticality above the landing board (see Fig. 1), the bee shadows are projected against the white background and also recorded. Shadows could be a significant problem in bee counting because a bee could be counted twice: the bee and its associated shadow. Additionally, a shadow could be present on the white background without the bee's presence in the image, depending on angle of the sun. The closer the bee is to the background, the darker the shadow will appear and could be detected whereas it corresponds to an outlier.

Table 1: Minimum length of bees and image resolution.

Image resolution	1080p	720p	540p	320p
Length of bees	56 pixels	37 pixels	29 pixels	19 pixels

The blue color of the sky is due to Rayleigh scattering. As the light moves through the atmosphere, most of the wavelengths pass straight through. However, much of the shorter wavelength light is absorbed by the gas molecules (Adeline et al., 2013). The absorbed blue light is then radiated in different directions, and, the sky looks blue. It gets scattered all around the sky and contributes to the illumination of objects in the natural shadow (i.e., hidden from the sun). This scenario assumes that shadows are mainly illuminated by the sky light (Adeline et al., 2013). Consequently, in a natural environment, shadows have high saturation in blue channels and low intensity. Fortunately, bee are not blue, but rather brown, orange or yellow (in term of the pixel values). Thus, the white background remains very useful because shadows can be easily removed when color pixel contains more blue than the other colors (illustrated in Fig. 3(h)).

Four algorithms (Algo 1, 2, 3 and 4) are developed and compared, as presented in Table 2. Bees are detected by computing ellipses (Contours and Ellipses,). The ellipses are created after an thin edge detection and the thresholding (Canny, 1986). Large and too small ellipses are easily removed to avoid numerous outliers, their sizes depends on the image resolution (see Table 1). Concerning Algo 1, edges are extracted directly on the original image, creating ellipses in

Table 2: Different algorithms compared in this study.

Steps of the algorithm	Algo 1	Algo 2	Algo 3	Algo 4
Difference between I_{t-1} and I_t		✓		
Difference between I_M and I_t			✓	✓
Remove blue parts (shadows)				✓
Variance between each color channel V_c				✓
Binary images		✓	✓	✓
Edge detection (Canny, 1986) + thresholding + Fit ellipses (Contours and Ellipses,)	✓	✓	✓	✓
Concordance $\mathcal{C}$: Eq. 5	✓	✓	✓	✓

undesirable parts of the image and for shadows (as image in Fig. 2(a)). Algo 2 computes the difference pixel by pixel between I_t and I_{t-1}, respectively the images at time t and $t-1$, in order not detect objects without movements. The problem of shadows remains in this algorithm and some parts in the white background are not efficiently eliminated. Furthermore, when a bee is not moving much or remains statics, it does not appear using the image difference $I_{t-1} - I_t$, and, the tracking process will fail. Algo 3 considers a difference between I_t and I_M, a median image of several previous images (for example 30 previous frames). However, shadows are always present and some parts remain visible in the background, resulting in the creation of undesirable ellipses. Thus, Algo 4 also considers the difference between I_t and I_M, removes pixels that are mostly blue and pixels with a high variance V_c between each color channels:

$$V_c(x,y) = \frac{1}{n} \cdot \sum_{i=1}^{n} (c_i(x,y) - \mu(x,y)), \qquad (1)$$

with

$$\mu(x,y) = \sum_{i=1}^{n} \frac{c_i(x,y)}{n} \qquad (2)$$

where (x,y) represents the pixel coordinates and n corresponds to the number of channels c_i (3 in our case: Red, Green and Blue). Finally, Algo 4 correctly extracts bees in the image for pixels having a high variance V_c (brown, orange... pixels, and, removing white parts with small V_c, i.e., V_c less than a threshold) and no blue parts (i.e., shadows) followed by an image difference. The protocol described in the next subsection is applied to these four bee algorithms.

3.3 Tracking of Bees

Once the bees are detected, the next step consists on extracting the movement of these bees throughout the video, from their appearance to their disappearance. Standard objects trackers fail to follow the bees (Viola and Jones, 2001)(Bradski, 1998), because of their numbers in the image. Moreover, they appear at different scales, turn around themselves and bees all look the same. In this study, the general idea is to determine the assumed position of bees in the next image. It works thanks to its positions on the two previous images. This assumed position is compared with all the bees on the image to determine which one fits a particular bee the best. To determine this assumed position, information about the bees in the previous images of the video is required, such as its coordinates and orientations.

Considering one detected bee represented by an ellipse at time t: ε_t (see Table 2), the bee trajectory for the $t+1$ frame can be estimated by knowing the coordinates of the two previous positions of the bee. Indeed, represented by the center and the orientation of an ellipse, at time $t-1$: ε_{t-1}, the distance the bee travels for the frame at time $t+1$ can be estimated, and, the direction it moves $\mathcal{D}_A$ is estimated thanks to the orientation of ε_{t-1} and ε_t. Indeed, as illustrated in Fig. 4, if Θ_{t-1} is the angle of ε_{t-1}, and Θ_t of ε_t, by computing the angle difference $\Delta\Theta$, we can assume that the ellipse ε_A at time $t+1$ will shift in the direction $\mathcal{D}_A$. This direction corresponds to $\mathcal{D}_t$ the movement direction between ε_{t-1} and ε_t, adjusted by $\Delta\Theta$:

$$\begin{cases} \Delta\Theta = \Theta_{t-1} - \Theta_t \\ \mathcal{D}_A = \mathcal{D}_t + \Delta\Theta \mod 2\pi. \end{cases} \qquad (3)$$

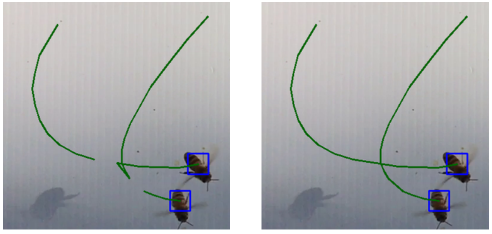
Thereafter, with $\mathcal{D}_A$ and the pixel distance between ε_{t-1} and ε_t, the assumed position of ε_A is estimated. Calling (X_{t-1}, Y_{t-1}), and (X_t, Y_t), respectively the coordinate of the ellipse centers at time t and $t-1$, thus, (X_A, Y_A), the assumed coordinate of ε_A are:

$$\begin{cases} X_A = X_t + (X_t - X_{t-1}) \cdot \sin(\mathcal{D}_A) \\ Y_A = Y_t + (Y_t - Y_{t-1}) \cdot \cos(\mathcal{D}_A). \end{cases} \qquad (4)$$

In the following step, the assumed ellipse ε_A is compared with all the real ellipses of the image at time $t+1$. For each real center of an ellipse, the distance between the center of ε_A is calculated. As illustrated in Fig. 4, the detected ellipse ε_{t+1} at time $t+1$ related to ε_t corresponds to which one has the minimal distance with the point at (X_A, Y_A), that corresponds to a concordance $\mathcal{C}$:

$$\begin{cases} \mathcal{C} = \min\sqrt{(X_A - X_D)^2 + (Y_A - Y_D)^2} \\ (X_{t+1}, Y_{t+1}) = \underset{(X_D,Y_D)}{\arg\min}\sqrt{(X_A - X_D)^2 + (Y_A - Y_D)^2}, \end{cases} \qquad (5)$$

(a) Frame 1 (b) Frame 4 (c) Frame 8 (d) Frame 12 (e) Frame 16



(f) Bee tracking without concordance (g) Bee tracking using concordance

(h)

Points in (h)	Red	Green	Blue	V_c
Shadow	91	95	**106**	3
Bee	123	88	106	11
Background	216	214	214	0.33

Figure 3: Comparison of bee tracking with and without concordance, 1080p, 60 fps.

where (X_D, Y_D) represents the coordinates of the center of the detected ellipse in the image at time $t+1$ and (X_{t+1}, Y_{t+1}) the coordinates of the center of ε_{t+1}. Figs. 3 (f) and (g) show the difference of a bee tracked with and without concordance.

If ε_t has no ellipse corresponding at time $t+1$, thus the bee is considered as moved out of the screen. When an ellipse at time $t+1$ has no corresponding ellipse from time t, it is assimilated as a new bee entering the screen. Finally, the higher the frame rate is important the most accurate this method is.

3.4 Bee Counting

The final stage in the bee tracking is to count the number of bees. Bees are identified in term of three different behaviors:

- fly in the beehive: entrance
- fly out the hive: departure
- flying by the hive.

These three entities define the in-and-out activity. To find the number of bees that come into the camera range, the purpose is to count the number of bee paths that the tracking algorithm has drawn. As illustrated by the results, the tracking method using Algo 4 seems robust: even though bees are really close to each other or fly in the same direction, there can be only one path per bee; bee counting would be as accurate as the bee detection is. The three behaviors imply there are three different paths which are drawn using three different colors, as detailed in Fig. 5. To determine their status (entrance, departure or passing by), the algorithm compares where each path begins and ends. To add an entrance, a bee must come from the outside zone and cross the area of the hive entrance at the end of its trajectory. On the contrary, to add a departure, the insect must leave the entrance of the hive at the beginning of its flight, then disappear beyond the outside zone. To be considered that a bee flies by, it must cross two times the outside zone. By the end, the algorithm returns a specific state for 100% of the detected bee paths.

4 EXPERIMENTAL RESULTS

The algorithms Algo 1, 2, 3 and 4 are coded in Python and use the OpenCv library. They are compared using 4 videos: 2 videos with 30fps and 2 with 60fps. These different videos, edited with four different image qualities (i.e., resolutions, see Tab. 2), have been used with the four presented algorithms: 1080p, 720p, 540p and 360p. The ground truth was obtained by five humans evaluators who counted the number of bees in the videos. Each algorithm has to run with every video in the four different sizes and different fps. The results are recorded in Tables 3, 4, 5 and 6. In tables are also reported the Mean of C in pixels ; the more the image size is large, the more the concordance must be high. Bees are moving fast in the video, often several dozens of pixel, so the results are better concerning videos with 60fps. Algo 4 is more precise in term of bee entrance and departure. Bees are counted several times in flyby, as the trajectory has been lost. However, the most important is to count as precisely as possible their inputs and departures, as Algo 4.

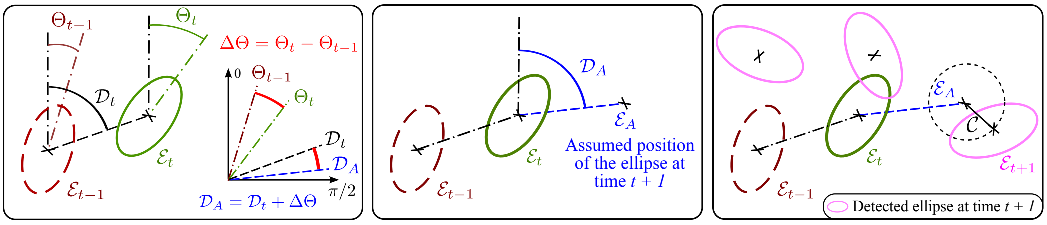


Figure 4: Concordance computation between the assumed ellipse and a detected one.

Table 3: Results on video 1 with 30fps, 429 frames.

	1080p Detection Ratio		720p Detection Ratio		540p Detection Ratio		360p Detection Ratio	
Algo 1	Entrances	2/7	Entrances	2/7	Entrances	3/7	Entrances	5/7
	Departures	2/12	Departures	2/12	Departures	2/12	Departures	4/12
	Flyby	9/19	Flyby	10/19	Flyby	8/19	Flyby	8/19
	Mean of $\mathcal{C}$	18,2	Mean of $\mathcal{C}$	11,6	Mean of $\mathcal{C}$	9,3	Mean of $\mathcal{C}$	6,4
Algo 2	Entrances	4/7	Entrances	4/7	Entrances	7/7	Entrances	7/7
	Departures	5/12	Departures	5/12	Departures	6/12	Departures	6/12
	Flyby	11/19	Flyby	12/19	Flyby	14/19	Flyby	15/19
	Mean of $\mathcal{C}$	16,6	Mean of $\mathcal{C}$	11,2	Mean of $\mathcal{C}$	8,1	Mean of $\mathcal{C}$	5,5
Algo 3	Entrances	4/7	Entrances	4/7	Entrances	6/7	Entrances	6/7
	Departures	5/12	Departures	5/12	Departures	5/12	Departures	5/12
	Flyby	11/19	Flyby	14/19	Flyby	14/19	Flyby	16/19
	Mean of $\mathcal{C}$	16,4	Mean of $\mathcal{C}$	10,8	Mean of $\mathcal{C}$	8,1	Mean of $\mathcal{C}$	5,5
Algo 4	Entrances	7/7	Entrances	5/7	Entrances	7/7	Entrances	7/7
	Departures	4/12	Departures	4/12	Departures	5/12	Departures	4/12
	Flyby	18/19	Flyby	14/19	Flyby	19/19	Flyby	21/19
	Mean of $\mathcal{C}$	15,0	Mean of $\mathcal{C}$	9,6	Mean of $\mathcal{C}$	7,4	Mean of $\mathcal{C}$	5,0

Table 4: Results on video 1 with 60fps, 858 frames.

	1080p Detection Ratio		720p Detection Ratio		540p Detection Ratio		360p Detection Ratio	
Algo 1	Entrances	2/7	Entrances	1/7	Entrances	2/7	Entrances	3/7
	Departures	2/12	Departures	2/12	Departures	2/12	Departures	3/12
	Flyby	12/19	Flyby	14/19	Flyby	17/19	Flyby	16/19
	Mean of $\mathcal{C}$	7,5	Mean of $\mathcal{C}$	5,5	Mean of $\mathcal{C}$	4,2	Mean of $\mathcal{C}$	2,7
Algo 2	Entrances	6/7	Entrances	3/7	Entrances	4/7	Entrances	6/7
	Departures	7/12	Departures	6/12	Departures	6/12	Departures	8/12
	Flyby	11/19	Flyby	14/19	Flyby	16/19	Flyby	21/19
	Mean of $\mathcal{C}$	6,6	Mean of $\mathcal{C}$	4,4	Mean of $\mathcal{C}$	3,3	Mean of $\mathcal{C}$	2,3
Algo 3	Entrances	6/7	Entrances	5/7	Entrances	8/7	Entrances	9/7
	Departures	8/12	Departures	7/12	Departures	7/12	Departures	7/12
	Flyby	16/19	Flyby	17/19	Flyby	17/19	Flyby	20/19
	Mean of $\mathcal{C}$	5,2	Mean of $\mathcal{C}$	3,6	Mean of $\mathcal{C}$	2,7	Mean of $\mathcal{C}$	1,9
Algo 4	Entrances	7/7	Entrances	8/7	Entrances	8/7	Entrances	7/7
	Departures	7/12	Departures	8/12	Departures	7/12	Departures	9/12
	Flyby	20/19	Flyby	20/19	Flyby	20/19	Flyby	19/19
	Mean of $\mathcal{C}$	5,8	Mean of $\mathcal{C}$	3,6	Mean of $\mathcal{C}$	2,7	Mean of $\mathcal{C}$	2,3

Table 5: Results on video 2 with 30fps, 878 frames.

	1080p Detection Ratio		720p Detection Ratio		540p Detection Ratio		360p Detection Ratio	
Algo 1	Entrances	1/31	Entrances	0/31	Entrances	0/31	Entrances	1/31
	Departures	0/22	Departures	0/22	Departures	1/22	Departures	0/22
	Flyby	12/13	Flyby	13/13	Flyby	14/13	Flyby	16/13
	Mean of $\mathcal{C}$	18,1	Mean of $\mathcal{C}$	12,2	Mean of $\mathcal{C}$	9,1	Mean of $\mathcal{C}$	5,4
Algo 2	Entrances	17/31	Entrances	20/31	Entrances	16/31	Entrances	25/31
	Departures	4/22	Departures	9/22	Departures	11/22	Departures	13/22
	Flyby	23/13	Flyby	26/13	Flyby	21/13	Flyby	35/13
	Mean of $\mathcal{C}$	18,2	Mean of $\mathcal{C}$	12,2	Mean of $\mathcal{C}$	9,2	Mean of $\mathcal{C}$	6,3
Algo 3	Entrances	11/31	Entrances	20/31	Entrances	22/31	Entrances	24/31
	Departures	6/22	Departures	9/22	Departures	10/22	Departures	13/22
	Flyby	29/13	Flyby	21/13	Flyby	34/13	Flyby	32/13
	Mean of $\mathcal{C}$	17,7	Mean of $\mathcal{C}$	11,9	Mean of $\mathcal{C}$	8,8	Mean of $\mathcal{C}$	6,0
Algo 4	Entrances	26/31	Entrances	24/31	Entrances	20/31	Entrances	26/31
	Departures	13/22	Departures	16/22	Departures	15/22	Departures	14/22
	Flyby	21/13	Flyby	24/13	Flyby	29/13	Flyby	23/13
	Mean of $\mathcal{C}$	13,9	Mean of $\mathcal{C}$	9,4	Mean of $\mathcal{C}$	7,0	Mean of $\mathcal{C}$	4,6

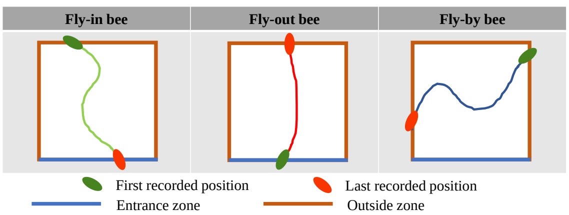
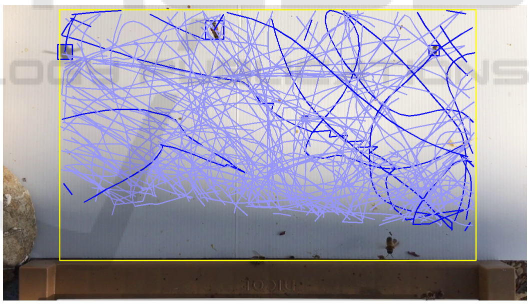


Figure 5: Device for the bee hive traffic monitoring.

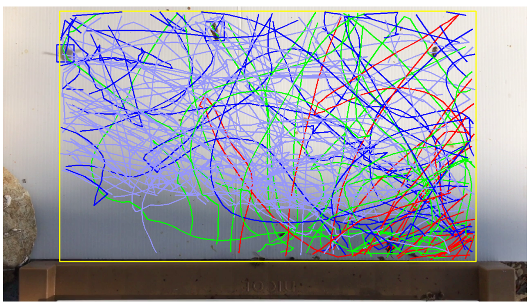
Table 6: Results on video 2 with 60fps, 1756 frames.

	1080p Detection Ratio		720p Detection Ratio		540p Detection Ratio		360p Detection Ratio	
Algo 1	Entrances	1/31	Entrances	0/31	Entrances	0/31	Entrances	0/31
	Departures	0/22	Departures	0/22	Departures	0/22	Departures	0/22
	Flyby	22/13	Flyby	17/13	Flyby	21/13	Flyby	22/13
	Mean of $\mathcal{C}$	7,0	Mean of $\mathcal{C}$	4,7	Mean of $\mathcal{C}$	3,3	Mean of $\mathcal{C}$	2,3
Algo 2	Entrances	13/31	Entrances	16/31	Entrances	18/31	Entrances	20/31
	Departures	9/22	Departures	17/22	Departures	20/22	Departures	23/22
	Flyby	45/13	Flyby	36/13	Flyby	44/13	Flyby	51/13
	Mean of $\mathcal{C}$	9,3	Mean of $\mathcal{C}$	6,2	Mean of $\mathcal{C}$	4,5	Mean of $\mathcal{C}$	3,1
Algo 3	Entrances	23/31	Entrances	23/31	Entrances	26/31	Entrances	28/31
	Departures	12/22	Departures	14/22	Departures	19/22	Departures	20/22
	Flyby	46/13	Flyby	43/13	Flyby	56/13	Flyby	56/13
	Mean of $\mathcal{C}$	8,2	Mean of $\mathcal{C}$	5,4	Mean of $\mathcal{C}$	4,0	Mean of $\mathcal{C}$	2,7
Algo 4	Entrances	31/31	Entrances	25/31	Entrances	30/31	Entrances	30/31
	Departures	22/22	Departures	23/22	Departures	23/22	Departures	23/22
	Flyby	27/13	Flyby	37/13	Flyby	35/13	Flyby	33/13
	Mean of $\mathcal{C}$	5,5	Mean of $\mathcal{C}$	3,7	Mean of $\mathcal{C}$	2,8	Mean of $\mathcal{C}$	2,0

Figs. 6 and 7 show bee tracking on a video at 720p, 60fps. Green lines corresponds to entrances, red to departures, blue to flyby and light blue to unresolved (see in Fig. 5). Contrary to algo 1, 2 and 3, bee shadows does not disturb the be tracking in the videos (see frames 6, 500, 1000 and 1755), exhibiting the interest of the proposed method.

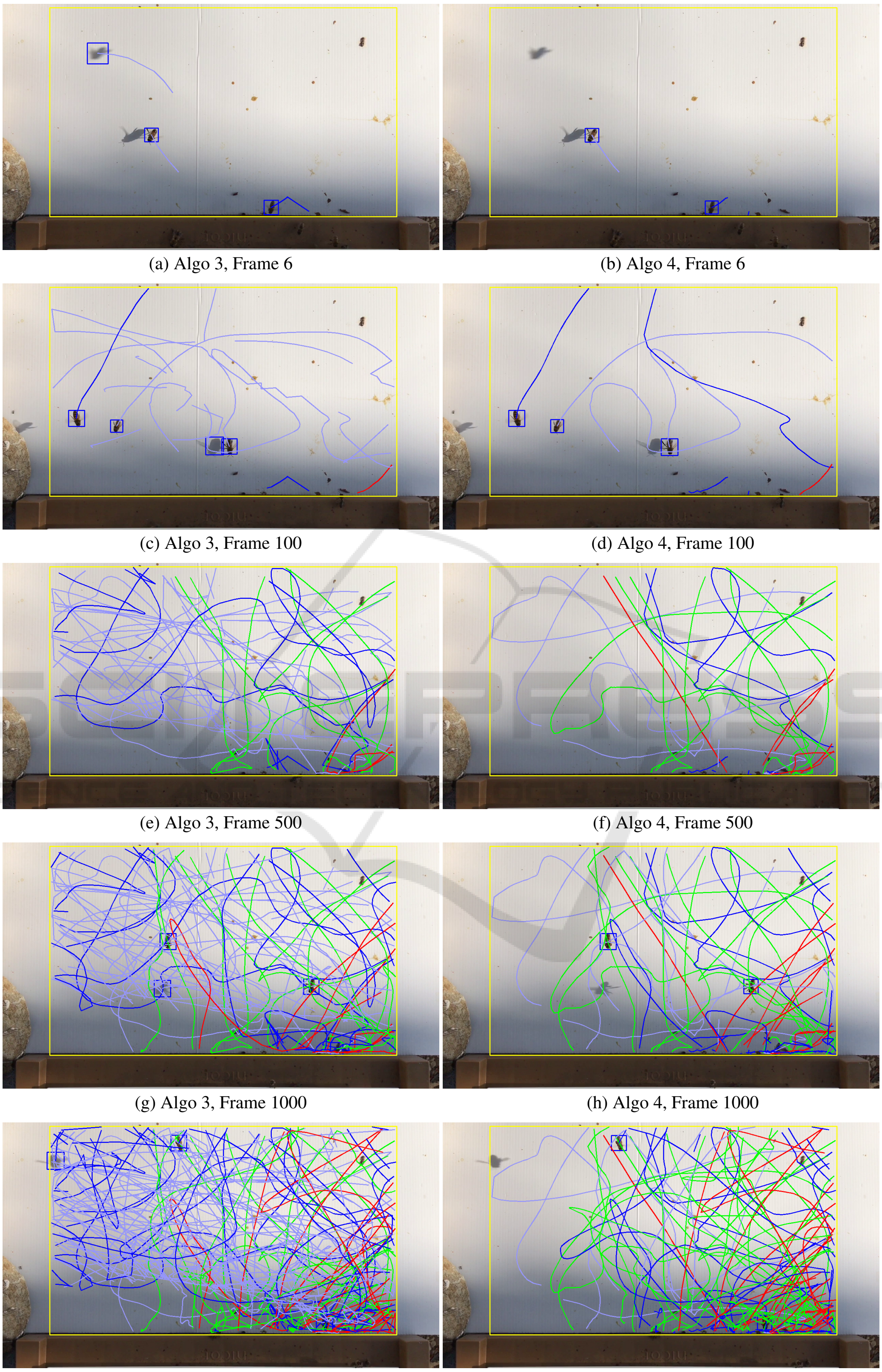


(a) Algo 1, Frame 1755



(b) Algo 2, Frame 1755

Figure 6: Bee tracking, video at 720p, 60fps.



(a) Algo 3, Frame 6 (b) Algo 4, Frame 6

(c) Algo 3, Frame 100 (d) Algo 4, Frame 100

(e) Algo 3, Frame 500 (f) Algo 4, Frame 500

(g) Algo 3, Frame 1000 (h) Algo 4, Frame 1000

(i) Algo 3, Frame 1755 (j) Algo 4, Frame 1755

Figure 7: Bee tracking using algo 3 and 4, video at 720p, 60fps.

5 CONCLUSION

This paper presents a simple and accurate way to count bees. The proposed approach combines different filtering methods to obtain new results on detection, tracking and counting bees. A particular attention has been given to the bee detection, without be disturbed by shadows. Indeed, variance treatment is used to improve bee segmentation, thus improving the tracking. Moreover, the concordance is used in the tracking step, which represents an elegant manner to follow fast objects in videos: the angular speed leads to the likelihood ellipse position. Quantitative experimental results show a precise detection of the bee entrances/departures. As this approach considers only a variance, edge detections, thresholds and ellipses, this new algorithm could be used in real-time process.

As future directions, we intend to implement these algorithm on nomad recording system to help beekeepers and researchers in their daily work. At the moment, this method gives quite good results but suffer from a too small fps. A possible enhance the detection is to integrate biggest camera angle to capture more bees on a larger white back ground.

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