

# Developing Ecological Sensors for Real-Time Interpretation of Honeybee Communication

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**Abstract**—This paper reports early success in using systems theoretic approaches to develop a real-time interpreter for honeybee communication. Foraging Western honeybees share location information of prime food sources through a particular dance. In this work we develop algorithms that translate time-series data of the dancing bees' locations into parameter estimates of the relevant food sources. The resulting system becomes a component in a future ecological sensor, *WaggleChat*, for deeper research into bee communication, demonstration of social insect communication to a broad audience, and a first step toward a new, closed-loop approach to pollination control for both agriculture and broader ecological management. Code, models, and more details are available at: <https://gitlab.com/idealabs/hb-comm-interpreter>.

## I. INTRODUCTION

Sensors are a control system's window to the world. As such, the development of novel sensors enables the application of control systems in new and more varied scenarios. The aim of this paper is to establish the foundations for ecological sensors to visually interpret the communication of honeybees within their hives in real time.

Forager Western honeybees, *Apis mellifera*, are able to communicate information to the colony about sources of nectar, pollen, water, or even new potential nest locations. They do this via a progression of cyclic movements known as the "waggle dance." The interpretation of this dance was established by ethologist Karl von Frisch in 1946 [1], leading to his winning the Nobel Prize in Physiology or Medicine in 1973, along with Konrad Lorenz and Nikolaas Tinbergen "for their discoveries concerning organization and elicitation of individual and social behaviour patterns" [2]. This work enabled researchers to interpret manually observed dances within observation hives, giving valuable insight into the health of both honeybee colonies and the surrounding environments which they pollinate.

What's more, the work of von Frisch stands as one of the most important milestones to date with regards to understanding non-primate communication and the rich ecological information network it represents [3]. Often such communication is chemical, making it more difficult to sense, but in some cases, like the waggle dance of *Apis mellifera*, the communication has a behavioral component that is amenable to visual sensors, provided appropriate signal processing can be developed to properly interpret the behavior patterns.

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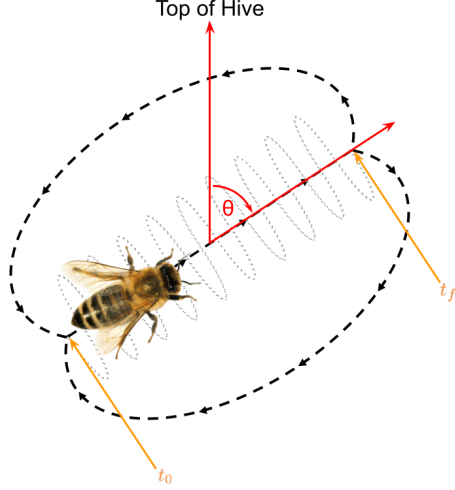
The aim of this work is to build upon the findings of von Frisch and his successors (see Related Work) to construct a sensor, including the necessary signal processing, for interpreting these waggle dances in real time. Such sensors will then enable a whole new class of ecological control systems relating to honeybee colonies.

## A. Motivation

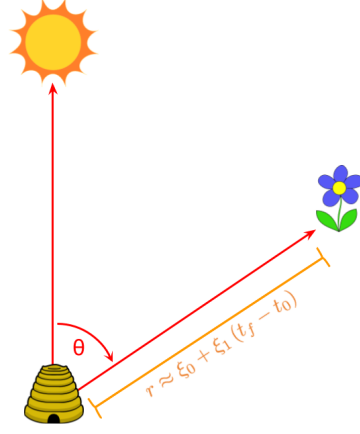
Pollinators perform an ecological function that is essential to the survival of all of Earth's terrestrial ecosystems. Of the 1,400 plant species cultivated worldwide for food and industry, nearly 80% require pollination by animals [4], including bees, butterflies, hummingbirds, etc. In some locations of the world, decreased local pollinator populations have forced human workers to pollinate fields by hand [5]. Estimates find the contribution of managed honeybee pollination to agricultural production to be between US\$28.0-122.8 million dollars, and the contribution of wild pollinators to be between US\$49.1-310.9 million dollars [6]. Improving current agricultural practices surrounding honeybees becomes increasingly important as the world witnesses the steady population decline of these remarkable insects [7].

Imagine that a sensor of the type we are attempting to construct is integrated into the honeybee hives of an industrial farm. The farm management team could utilize the tool to understand where the honeybees are pollinating, which food sources the honeybees consider to be better than others, and which areas of the farm the honeybees may be avoiding—and therefore not pollinating. As a result, the farm management team could then investigate these less-pollinated areas to discern whether action may be taken to encourage pollination in this area: pesticide use may be too high in that area of the farm; or perhaps honeybee predators, such as wasps, may have infected the area. Thus, the sensor provides feedback in the manual "human-in-the-loop" control loop between the farm biosphere and the farmer. An ecologist studying a specific environment may find such a sensor useful for the same purposes: the study and causes of pollination inefficacy.

The sensor may also be incorporated into a future automated control device, one that discerns where honeybees are pollinating using the sensor and then encourages honeybees to pollinate in areas that have yet to be pollinated through mechanical or olfactory means (potential work in this area is described in Related Work). Such a control device could be implemented on an industrial farm to improve pollination efforts, or by researchers to gain deeper insights into communication patterns among eusocial insects.



(a) The run angle  $\theta$ , the run starting time  $t_0$ , and the run finishing time  $t_f$  of a honeybee waggle dance.



(b) The angle to the food source  $\theta$  with respect to the sun and the distance to the food source,  $r$ .

Fig. 1. The angle to the food source with respect to the sun, with the hive at the vertex, is equivalent to the angle,  $\theta$ , of the waggle run; the distance to the food source,  $r$ , is a linear function of the run duration,  $\tau = t_f - t_0$  [8].

## B. Related Works

Couvillon presented a summary of von Frisch’s findings and advancements in the study of honeybee waggle dance communication through 2011 [9]. In 2012, Couvillon et al. established protocols for the efficient decoding of the waggle dance [10].

A German company [apic.ai](#), founded in 2018, is an industry leader in the development of electronic honeybee monitors. They produce sensors that monitor the entrance and exit of honeybees and bumblebees from a hive, the number and share of bees carrying pollen, the diversity of pollen carried by bees into the hive, the mortality rate of the hive, among other indicators. They published their findings on the large-scale monitoring of beehives, naming their system *DeepBees* [11].

In recent years, the development of computer vision technology has enabled the construction of several automated waggle dance interpretation systems. Wario et al. [12] developed a system *BeesBook* that monitors honeybees over extended periods of time and provides real-time interpretations of the waggle dances present; however, the *BeesBook* system requires black-and-white markers to be placed on the honeybees in order for the computer vision system to track them. In 2017, Wario et al. published an improvement on their previous system, a new system “capable of automatically detecting, decoding and mapping communication dances in real-time” [13]; this work, although adopting different techniques, is most similar to that reported here. In 2021, a combined team from the Okinawa Institute of Science and Technology Graduate University and the Australian National University published a method for the markerless tracking of all individuals in a bee colony with some post-processing required [14]; these results are accurate

but are not real-time.

Landgraf et al. developed a mechanical bee, named *RoboBee*, that performed the waggle dance and “elicited natural dance-following behavior in live bees”; through tracking the flight of bees in that colony, the team was able to confirm that the bees used the information encoded in the robotic waggle dance to locate food sources [15]. Such a tool, in combination with a sensor such as the one reported here, could be used for the construction of a complete automatic control loop that improves pollination efficacy in a given environment.

## II. BACKGROUND ON HONEYBEE COMMUNICATION: THE WAGGLE DANCE

Upon discovering a food source that is farther than 100 meters from its resident hive, a forager honeybee will begin a cyclic “waggle” dance that follows the following form [8]: (see Fig. 1a)

- 1) The forager bee walks in one direction along a linear path, “wagging” its abdomen from side to side as it progresses along this path. (This portion of the dance is referred to in the literature as the *run* or *waggle run*.)
- 2) The forager then turns either to the left or to the right, circling around to return to the start of the waggle run. (This portion of the dance is referred to as the *return*.)
- 3) The forager repeats the waggle run with the next return being to the opposite side.

This dance is repeated anywhere from one to more than a hundred times, alternating between a right and left return after each run [9]. Surrounding forager bees hug close to the dancing forager bee in order to feel out the pattern of the bee’s dance [8].

As stated previously, Karl von Frisch discovered that this dance encodes geographical information about the location

and quality of an identified food source [1] (see Fig. 1b). When the waggle dance is performed on a vertical surface (e.g., inside a vertically situated hive), the angle from the top (upwards) of the hive to the linear path of the waggle run is equal to the angle from the sun to the located food source with the hive being the vertex of this angle; the duration of the waggle has a linear relationship with the distance from the hive to the located food source; and the “liveliness” (a vague and yet to be officially standardized measurement that describes the vigor and excitement of the bee’s wagging vibrations along the run) of the dance has a positive linear relationship with the profitability of the food source—which includes factors such as the source’s sweetness, purity, viscosity, fragrance, and ease of access [8].

Thus, when a forager bee locates a food source and returns to the hive, its waggle dance signals a communication vector  $v(t)$  to the surrounding bees, defined as follows:

$$v(t) = [\theta(t) \quad r \quad q]^T, \quad (1)$$

where  $\theta(t)$  is the angle to the located food source with respect to the location of the sun at time  $t$ ;  $r$  is the distance to the food source in kilometers; and  $q$  is a profitability-of-food-source coefficient.

Furthermore,  $r$  can be approximately expressed as

$$r \approx \xi_0 + \xi_1 \tau, \quad (2)$$

where  $\xi_0$  and  $\xi_1$  are fit coefficients, and  $\tau = t_f - t_0$  is the duration of the run in the forager bee’s waggle dance. Using the data presented by Karl von Frisch [8],  $L_2$ -regression yields values  $\xi_0 = -0.0562$  and  $\xi_1 = 1.245$  for Eq. 2.

Surrounding honeybees following one of their sister’s dances compensate for errors in the dance by averaging the run direction and duration across multiple runs [16]. The number of runs averaged by the sister bees may vary, but in this work we follow the protocol established in [10].

### III. PROBLEM FORMULATION

Given a video of vertically positioned honeybee comb, we aim to extract the dance communication vectors  $v_1, \dots, v_c$  of the  $c$  waggle dances being performed by honeybees on the comb within the video. We decompose this problem into four subproblems:

- 1) identification of a honeybee performing the waggle dance;
- 2) tracking of that dancing honeybee across the video;
- 3) classification of the honeybee’s locations over time as being on the waggle run or the return; and
- 4) estimation of the dance angle and duration.

#### A. Identification of a Dancing Bee

First, given a video—a sequence of images  $I_0, \dots, I_n$ —of vertically positioned honeybee comb, we want to identify a honeybee performing the waggle dance out of the set of all bees  $B$  on the comb surface present in the images  $I_0, \dots, I_n$ .

This task will be addressed in a future paper. For now, we assume that a dancing honeybee has been identified in

the video and that its horizontal and vertical location (in pixels)  $x_0 \in \mathbb{R}^2$  in image  $I_0$  has been identified as part of pre-processing.

#### B. Tracking a Dancing Bee

Given the identified dancing honeybee and its location  $x_0 \in \mathbb{R}^2$  in the first image  $I_0$ , we want to identify the subsequent locations  $x_k \in \mathbb{R}^2, k = 1, \dots, n$  of the honeybee in each image  $I_k, k = 1, \dots, n$ , respectively. The problem here is to map from video data to quantified position data.

For the purposes of this paper, we utilized hand-annotated locations of dancing bees from 25 different videos pulled from YouTube. However, it is important to note that Bozek et al. [14] have developed a machine learning method for the markerless tracking of individual honeybees, albeit with some post-processing time required.

#### C. Real-Time Classification of the Waggle Run

Given each location  $x_k, k = 0, \dots, n$  of the dancing bee over time, we want to identify the function  $y_k = g(x_0, \dots, x_k, \dots, x_n) \in \{0, 1\}$  that maps the locations  $(x_0, \dots, x_n)$  of the dancing bee to the classification of point  $x_k$  as being on either *the waggle run* (labeled  $y_k = 1$ ) or *the return* ( $y_k = 0$ ). Our solution to this subproblem is presented in Section IV.

#### D. Real-Time Estimation of the Run Angle and Duration

Given each location  $x_k, k = 0, \dots, n$  of the dancing bee over time and the respective classifications  $y_k, k = 0, \dots, n$  of those locations, we want to:

- 1) identify all waggle runs  $R_1, \dots, R_\omega$ —sequences of locations  $x_k$  that are all classified as  $y_k = 1$ ;
- 2) extract the angles  $\theta_1, \dots, \theta_\omega$  of each of these waggle runs; and
- 3) compute the duration  $\tau_1, \dots, \tau_\omega$  (in seconds) of each of these waggle runs.

By solving the above problem, we are extracting information that encodes the angle  $\theta$  and distance  $r$  of the dance communication vector  $v$  for the dance performed by honeybee. Our solution to this subproblem is presented in the Section IV. In this work we will not attempt to estimate the third element, the profitability-of-food-source coefficient,  $q$ , since there is no unified view in the literature about how to quantify the “profitability” of a food source to include sweetness, purity, viscosity, fragrance, ease of access, etc. [17], [18], [9]; we leave that to future work.

## IV. SOLUTIONS

#### A. Real-Time Classification of the Waggle Run

To classify each location  $x_k$  as being on either *the waggle run* (labeled  $y = 1$ ) or *the return* ( $y = 0$ ), we defined two features  $\bar{d}_k$  (mean consecutive distance) and  $\bar{\alpha}_k$  (mean consecutive supplementary angle) to be used in a Logistic Regression algorithm. The mean consecutive distance  $\bar{d}_k$  for time step  $k$  is given by

$$\bar{d}_k = \frac{1}{6} \sum_{j=k-2}^{k+3} d_j, \quad (3)$$

where

$$d_k = \frac{1}{\hat{h}} \cdot \|x_k - x_{k-1}\|_2, \quad (4)$$

and  $\hat{h}$  is the mean length of a honeybee (in pixels) in the video (measured in a pre-processing and calibration step). The mean consecutive supplementary angle  $\bar{\alpha}_k$  for time step  $t = k$  is given by

$$\bar{\alpha}_k = \frac{1}{5} \sum_{j=k-2}^{k+2} \alpha_j, \quad (5)$$

where

$$\alpha_k = \frac{1}{\pi} \cdot \arccos \left( \frac{\frac{1}{\hat{h}} \cdot \|x_{k+1} - x_{k-1}\|_2^2 - d_{k+1}^2 - d_k^2}{2 \cdot d_{k+1} \cdot d_k} \right). \quad (6)$$

The Logistic Regression algorithm, after being fit to pre-labeled data points (part of the pre-processing and calibration step), then produces the following classifier for the waggle run and return:

$$\hat{y}_k = \left\lfloor \left( \frac{1}{1 + e^{-A^T \hat{\beta}}} \right) + \frac{1}{2} \right\rfloor \in \{0, 1\}, \quad (7)$$

where  $A = [1 \ \bar{d}_k \ \bar{\alpha}_k \ \bar{d}_k \cdot \bar{\alpha}_k]^T \in \mathbb{R}^4$  is the input data, including the mean consecutive distance, mean consecutive supplementary angle, and their interaction; and  $\hat{\beta} \in \mathbb{R}^4$  are their respective coefficients. Using videos with a frame rate of between 24-30 fps, we pre-fit the coefficients using  $L2$ -regression to get  $\hat{\beta} = [-7.38618922 \ 10.67163016 \ 9.50486566 \ 6.89406401]^T$ .

Due to the dependency of the classification  $\hat{y}_k$  of location  $x_k$  on previous points  $x_{k-3}, \dots, x_{k-1}$  and future points  $x_{k+1}, \dots, x_{k+3}$ , the classification algorithm will not classify the first three points  $x_0, x_1, x_2$  and the last three points  $x_{n-2}, x_{n-1}, x_n$  in a video.

**Smoothing Operator for Classified Points:** Because waggle runs and returns only occur in longish sequences, we can employ a smoothing operator to correct any small windows of points that are misclassified. That is, points clump together in runs and returns, so any spurious run-points in the middle of a return sequence, or vice versa, can be corrected with appropriate smoothing.

We begin by deciding the maximal sequence length,  $l_{max}$ , that we think might be spurious. We will then use the data surrounding sequences of these lengths to decide whether to reclassify them or not. In this work we consider sequences up to length  $l_{max} = 8$  on data collected at 24-30 fps as being potentially spurious. With  $l_{max}$  defined, we then iterate through the data considering sequences of length  $l = 1, 2, \dots, l_{max}$ , and with a clever software implementation the operations for different lengthed sequences can be designed to work with only one pass through the data.

To correct for sequences of  $l \leq l_{max}$ , we simply consider the  $l + 1$  points prior to the sequence (i.e. the *presequence*), and the  $l + 1$  points immediately following the sequence (i.e. the *postsequence*), and assign all  $l$  points of the sequence to be the most common value in the pre-and-post sequences. So, for example, if we are considering a sequence of five ones (where one indicates points along a waggle run), we look at the presequence of six points and the postsequence of six points and see what value is most common. If these twelve points are mostly zeros (indicating points on a return path, not a waggle run), then we flip the value of the five points in the sequence from one to zero and assume that they were misclassified.

### B. Real-Time Estimation of the Run Angle and Duration

A series of  $\rho$  consecutive points  $x_j, \dots, x_{j+\rho-1}$  that are all classified as on the waggle run ( $\hat{y}_j, \dots, \hat{y}_{j+\rho-1} = 1$ ) can be considered a collection of points that is a single waggle run  $R$ . We collect and store each of the runs  $R_1, \dots, R_\omega$  that occur throughout the video.

For each run  $R_i$ , we then use total least squares to fit a straight line to the midpoints  $\frac{x_{j+1}+x_j}{2}, \frac{x_{j+2}+x_{j+1}}{2}, \dots, \frac{x_{j+\rho-1}+x_{j+\rho-2}}{2}$  of each consecutive pair of points in the run. (Fitting the line to the midpoints removes the “wagging” portion of the signal, allowing us to better follow the bee’s linear path of travel; the efficacy of this approach, as opposed to simply fitting the line to the original locations  $x_k$ , is demonstrated in Fig. 2.) We then determine the direction of the bee’s travel by extracting the projections  $\nu_1$  and  $\nu_\rho$  of the first midpoint  $\frac{x_{j+1}+x_j}{2}$  and last midpoint  $\frac{x_{j+\rho-1}+x_{j+\rho-2}}{2}$  onto the fitted line. The angle of the waggle run  $\hat{\theta}_i$  is then computed as follows:

$$\hat{\theta}_i = -(\text{atan2}(\nu_\rho - \nu_1) - 90) \quad (8)$$

At this stage we also calculate the duration  $\hat{\tau}_i$  of each sequence. This is calculated as

$$\hat{\tau}_i = \frac{\rho_i}{f} \quad (9)$$

where  $\rho_i$  is the duration of waggle run  $R_i$  (in frames), and  $f$  is the frame rate of the overall image sequence  $I_0, \dots, I_n$  (in fps).

In accordance with the protocols established by Couvillon et al. [10] for efficiently decoding honeybee waggle dances, we take the mean of an even number  $\hat{\omega} \bmod 2 = 0$  of the  $\omega$  computed run angles  $\hat{\theta}_1, \dots, \hat{\theta}_\omega$  to produce an estimated angle  $\hat{\theta}$  to the food source. (The last run is included or excluded to ensure that the mean is taken across an even number of runs.) Runs with much shorter run durations (outliers) are also excluded. Similarly, we take the mean  $\bar{\tau}$  of the run durations  $\hat{\tau}_1, \dots, \hat{\tau}_\omega$  to then produce the estimated distance  $\hat{r} = -0.562 + 1.245\bar{\tau}$  to the food source, where, as we described in Section II, the coefficients  $-0.562$  and  $1.245$  were calculated from Dr. von Frisch’s interpretation of his original data.

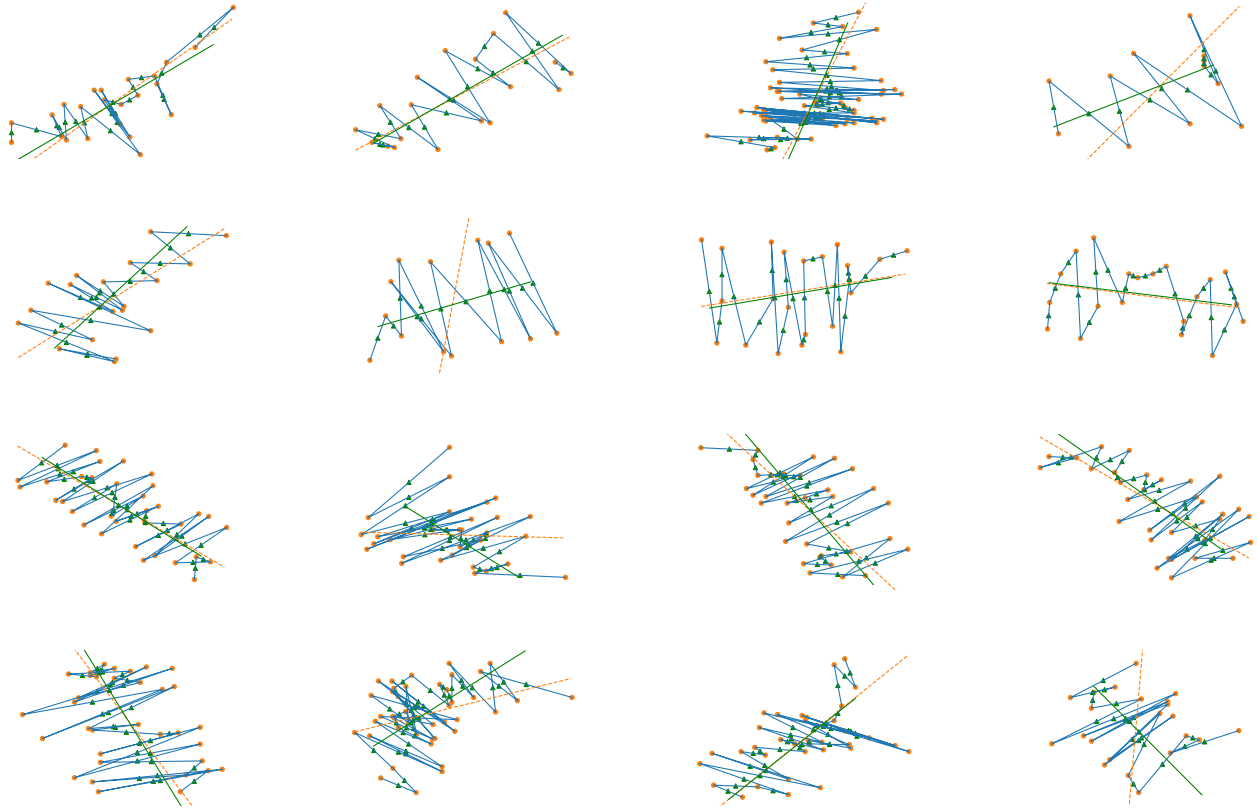
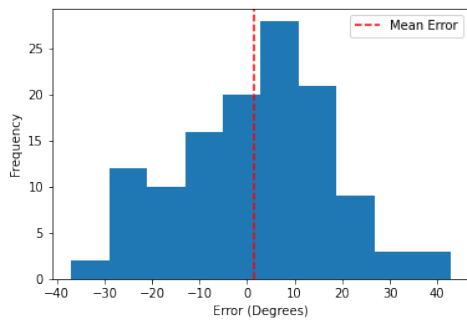
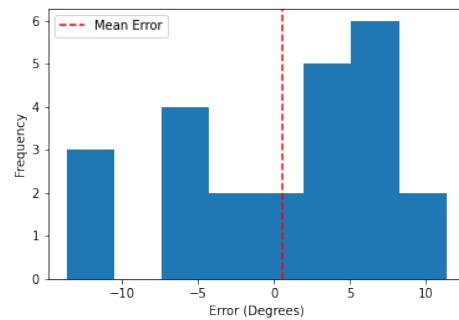


Fig. 2. Data from 16 of 124 total waggle runs annotated for this study. (Human annotated) position data is reflected as orange circles connected by blue lines, showing how the points follow each other in sequence. Green triangles indicate midpoints between consecutive pairs of data points, and the green solid line is the best total-least-squares fit to the midpoint data. Compare this to the orange dashed line, which is the total least squares fit or first principal component of the raw position data, which sometimes can go drastically awry.



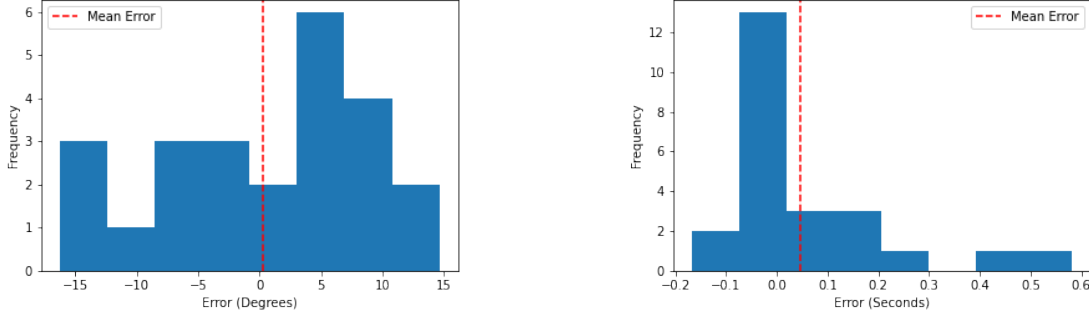
(a) Histogram of the error between the estimated angle of the 124 waggle runs and the human annotated ground truth angle. The vertical dashed red line indicates the mean error of 1.555 degrees and a standard deviation of 15.902.



(b) Since many waggle runs are repeats of the same forager bee trying to communicate the same information in a single waggle dance, this histogram reveals the distribution of error in angle estimation when runs from the same dance are averaged together. Notice the smaller spread in the error distribution.

Fig. 3. Error distribution of estimated angle using data classified as "run" data by human annotation, comparing to human annotated angle, and using human annotated position data to drive the estimation algorithm.





(a) Error distribution of estimated angle from waggle runs averaged over runs from the same waggle dance. Compare with Figure 3b, which used human classification instead of algorithmic classification. As with the other histograms in Figures 3 and 4, the vertical red dashed line indicates the mean of the distribution.

(b) Error distribution of duration from waggle runs averaged over runs from the same waggle dance. Since duration effectively subtracts the timestamp of the first data point from that of the last data point labeled as “run” data, this distribution essentially is another view of the classification error of our logistic regression and smoothing algorithm.

Fig. 4. Error distribution of estimated angle using data classified as “run” data by logistic regression, comparing to human annotated angle, and using human annotated position data to drive the estimation algorithm.

## V. RESULTS AND DISCUSSION

We have divided our results into three sections:

- 1) an independent analysis of the quality of our classification algorithm on 25 different labeled waggle dance videos pulled from YouTube;
- 2) an independent analysis of the quality of our estimation algorithm on the same 25 dances; and
- 3) a combined analysis of the classification and estimation algorithm working in tandem on the same 25 dances.

### A. Real-Time Classification of the Waggle Run

When run on hand-annotated locations  $x_k$  from the 25 videos of waggle dances pulled from YouTube, the Logistic Regression classifier achieved a classification accuracy of 93.00%. The smoothing operator boosted this classification accuracy to 95.39%.

### B. Real-Time Estimation of the Run Angle

When run on hand-annotated locations  $x_k$  and classification labels  $y_k$  from the pulled YouTube data, our estimation algorithm has an average error of  $1.555^\circ$  with a standard deviation  $\sigma = 15.902$  for the angle  $\hat{\theta}_i$  of each waggle run  $R_i$  (the error distribution is pictured in Fig. 3a). However, when we average the estimated run angles  $\theta_i, i = 1, \dots, \omega$  across the entire dance, then the error in our estimate for the dance angle  $\hat{\theta}$  reduces to  $0.532^\circ$  with a reduced standard deviation  $\sigma = 7.015$  (distribution pictured in Fig. 3b). Thus, although there may be higher variation and bias in the estimates from run to run, the algorithm is much more accurate when extracting information for an entire dance.

### C. Combined Classification and Estimation

When the classification algorithm and the estimation algorithm are run sequentially, with the hand-annotated locations  $x_k$  pulled from the YouTube data fed into the classifier and the output classifications  $\hat{y}_k$  fed into the estimator, the mean

error in our estimated angle  $\hat{\theta}$  for each waggle dance is  $0.308^\circ$  with a standard deviation  $\sigma = 8.797$  (the distribution of dance angle error is pictured in Fig. 4a). Thus, the classifier and estimator together perform with slightly less bias and only slightly greater variance than the estimator alone on hand-labeled classifications. Similarly, the error in our estimated waggle duration  $\hat{\tau}$  for each waggle dance is 0.047 seconds with a standard deviation  $\sigma = 0.169$  (the distribution of dance duration error is pictured in Fig. 4b).

## VI. CONCLUSIONS AND FUTURE WORK

This paper describes the problem of automating the extraction of information communicated by a honeybee engaged in a waggle dance. We identified four subproblems: 1) identifying a dancing bee, 2) tracking a dancing bee, 3) classifying position data from the bee as either part of the waggle “run” or “return,” and 4) estimating the run angle and duration. In this paper we ignored the first and second subproblems, assuming they had already been solved (a solution for the second subproblem requiring some post-processing time has been reported in the literature [14]). We then focused on solving the third and fourth subproblems, classification and estimation, and demonstrated on data from 124 waggle runs the efficacy of our solutions. These results lay the foundation for development of ecological sensors for real-time interpretation of honeybee communication.

This work is part of our larger research effort solving all four subproblems and using the resulting ecological sensors for pollination control. To work on these problems, we’ve developed an experimental platform consisting of the setup shown in Fig. 5. Located within the Brigham Young University Life Science Greenhouses, we set up an observation hive during the summer of 2021 and relocated a colony of Italian Western honeybees (*Apis mellifera ligustica*) into the hive. We also purchased two Logitech StreamCam Plus cameras and a custom-built computer with an RTX 3090 GPU and

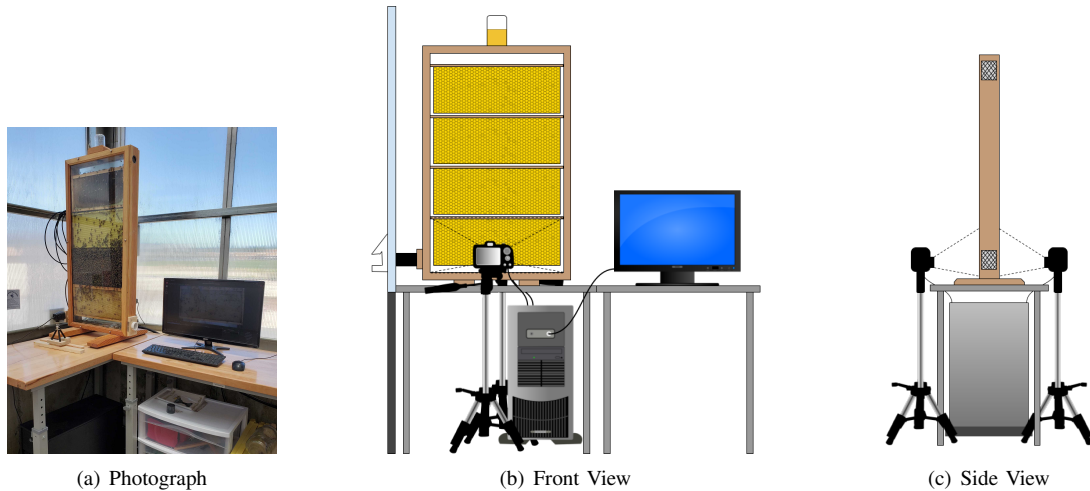


Fig. 5. The observation hive and camera-computer system setup at the Brigham Young University Life Science Greenhouses.

Ryzen 9 5900X CPU. Our goal is to have a fully constructed honeybee dance interpreter, named *WaggleChat*, that works in real time by fall of 2022. To accomplish this, we will be expanding on the work achieved by Wario et al. [13], Bozek et al. [14], and Marstaller, Tausch, and Stock [11] to create a real-time markerless tracking system to track honeybees. We will then apply the algorithms presented in this paper to automatically decode any waggle dances that occur. A live view of the bottom frames of the observation hive provided by the cameras (see Figs. 5b, 5c) can be accessed via the following link: [bees.byu.edu](https://bees.byu.edu).

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