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Bio-Inspired Visual Navigation for a Quadcopter using Optic Flow

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Small Unmanned Air Vehicles (UAVs) have become increasingly used in many fields to keep up with demands for technological growth and due to their unique ability to provide an "eye-in-the-sky". However, traditional guidance systems are not always suitable for a transition to smaller UAVs. Honeybee navigation has long been proposed as a basis for developing navigation for robotics as they are known to solve complex tasks efficiently and robustly. An approach for bio-inspired navigation using optic flow is presented here based on honeybee reactive flight control. This approach is tested and verified in the benchmark hallway navigation problem. It is shown that the control approach can explain a wide-range of biological behaviors using minimal sensors similar to flying insects.

I. Introduction

Increasingly over the years, autonomous Unmanned Aerial Vehicles (UAVs) are being used to perform missions that are considered "dull, dirty, and dangerous", such as operations in nuclear power plants, agricultural monitoring, wild-fire surveillance, border patrols, and weather forecasting [1]. This is due to UAV's unique ability to provide an "eye-in-the-sky" and collect data from countless different sensors. Due to progress in the miniaturization of electronics, UAVs are becoming much smaller (<20 lb) and more affordable. Advances in sensors, processing, and batteries have made these technologies low-weight, low-power, and low-cost and allowed these small UAVs (sUAVs) to broaden their user group and applications.

The complications of flight for air vehicles are especially compounded for sUAVs. They are more likely to operate in complex missions (such as searching buildings or other confined areas) due to their agile nature and are much more heavily affected by small changes in their environment. Since they are more likely to fly at lower altitudes, variations in terrain need to be taken into consideration. Additionally, wind is a constant challenge as sUAVs fly at a much "slower" airspeed of about 10-20 meter/second. At 50-100 meters above ground level, wind is already about 5-10 m/s depending on conditions which means that sUAVs can easily be thrown off course. Furthermore, the reduced payload capabilities of small UAVs mean that heavy sensors and processors often cannot be utilized. It is frequently the case that GPS is unavailable or imprecise, state estimators are inaccurate, and that weight restrictions don't allow for the redundancy of multiple sensors.

The limitations imposed by these constraints are especially acute if the UAV includes a human in its control loop. A key factor limiting UAV growth is therefore their ability to display autonomous and intelligent control with little human intervention [2]. The study of flying insects is interesting from the point of view of sUAV design, because they share similar constraints (i.e. small size, low weight, and low energy consumption). There has been extensive research in this area in order to enable robots with similar capabilities and with comparable efficiency [3].

This research exploits the knowledge of honeybee visual navigation to develop a bio-inspired control architecture for a sUAV. This paper gives the biological inspiration and current state-of-the-art, presents the navigation task, describes the adapted control methodology, and presents and discusses experimental results.

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II. Honeybee Navigation for UAV Control

Despite their relatively small brains, individual social insects of many species have surprisingly advanced cognitive abilities and in particular, a great capacity for learning. These abilities are especially well demonstrated in the honeybee Apis mellifera. In particular, there has been extensive research in recent years into honeybee vision and flight navigation as bees are known to have impressive capabilities in these regards. For example, honeybees will seek out food over many miles and directly return to their hive, provide navigational instructions to each other, use landmarks for location identification, distinguish colors to identify good sources of food, navigate in corridors and other, complex environments, and more [3].

Though much focus is on replicating experimental and theoretical navigation of honeybees, the mechanisms described are very similar in other flying insects [4]. Flying insects are capable of agile flight at low speeds, complex obstacle avoidance, vertical take-off and landing, and hovering for long periods at a time. Insects are partially capable of such a wide range of tasks despite their small brain size, because they are able to detect motion in their visual field using Elementary Motion Detectors (EMD) to discern Optic Flow (OF). This optic flow encodes information about the angular velocity at which any environmental feature moves past the visual field and can be used to estimate motion of an object. Recent studies have shown that the optic flow visual processing capabilities of honeybees can be used to control their course, estimate distance travelled and flight duration, avoid obstacles, regulate flight speed, and land smoothly [5-8].

One of the bee's most impressive features is its ability to navigate with limited sensory feedback. Sensors used in navigation for flying insects mainly include the chemical sensors, halteres, and compound eyes and their constituent ocelli. Honeybee olfaction plays an important role in bees' daily lives and is what allows them to communicate with each other, detect dangers, and forage on thousands of flowers in their lifetime as it is the primary sense used to differentiate flowers. Odor detection primarily takes place on the bees' antennae where the olfactory system has two tracks to provide two separate bits of information: (1) general information about what the odor is and (2) more specific information about where and when the odor occurred [9]. It is likely this parallel processing which allows navigation to odors cues despite the complexity of many mixed odors [10]. Aside from optic flow detection, the compound eyes provide information for object and landmark recognition, fixation, and heading corrections [11]. In addition to reactive heading corrections, bees use a sun compass for navigation and the ocelli play a role in providing this information [12]. Finally, the halteres are the biological equivalent of a gyroscope and provide estimated feedback about body angular velocities [13].

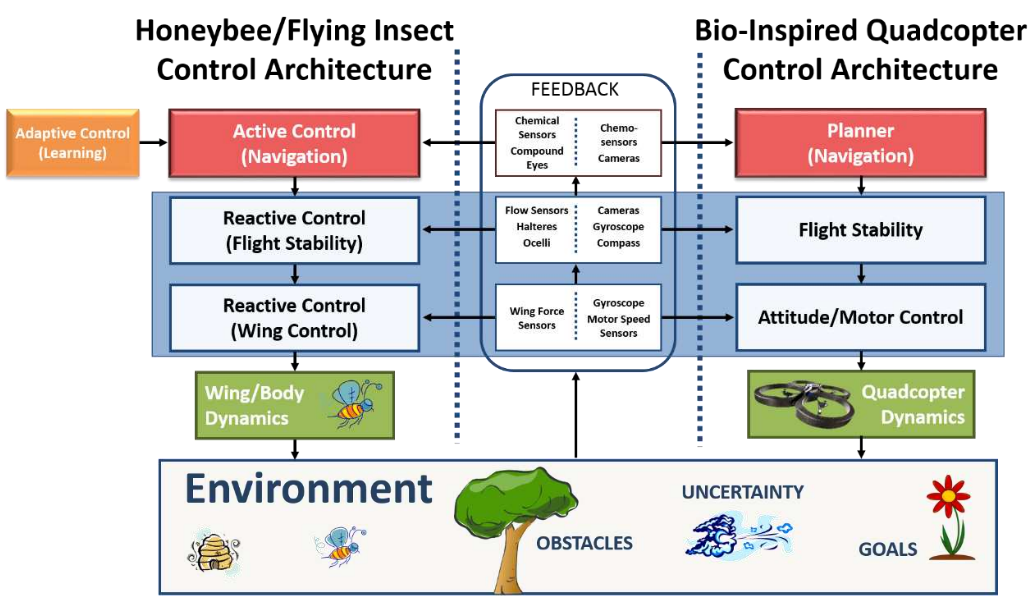

Figure 1: Bio-Inspired Control Architecture for a Quadcopter*

Currently, little is known about the physiology behind flight control mechanisms [14-15]. Experiments suggest that there are at least two levels of control and that these can be summarized as: lower-level, reactive control and higher-level, active navigation control (see Figure 1) [16]. For low-level control, the halteres, ocelli, and flow feedback from the compound eyes are used to stabilize flight by mediating corrective reflexes. For high-level control, odor cues and visual feedback are sent to the mushroom bodies for action-selection and learning [17].

There is a lot of interest in the sUAV community to develop reactive control for better low-level autonomy so as to free up mission control to make better high-level decisions [16]. Figure 1 above shows the parallels in insect sensing and control with a bio-inspired scheme for sUAVs; the focus in this research is on reactive control. The control using optic flow by bees is often investigated by their capability to navigate in corridors (see Figure 2 below). The behavior in bees (and therefore, the control development discussed in the next section) are largely explained by three simple rules: (1) maintain lateral position by balancing the angular velocity in the left and right eye, (2) uphold forward velocity by regulating the total angular velocity against an empirical setpoint, and (3) adjust altitude by balancing the ventral angular velocity against an empirical setpoint [18-19]. When the environment is static, the optic flow is approximately equal to the angular velocity, and these terms are often used interchangeably.

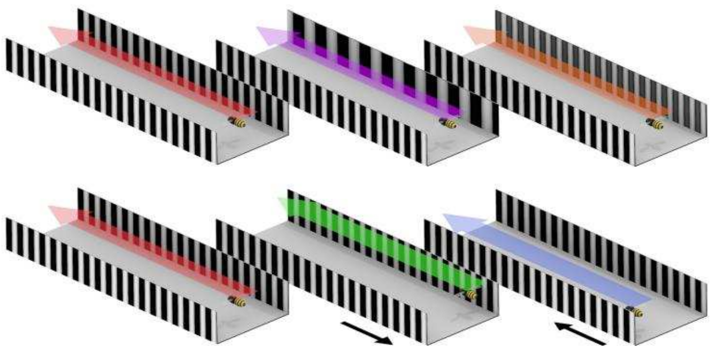

Figure 2: Navigation of a Honeybee in a Corridor for Visual Input with Varying Spatial Frequencies [20]

The mechanisms behind these behaviors in bees are studied and often implemented on robots so as to better understand them. Optic flow-based control applications have been demonstrated with limited performance under constrained operational situations. Most successful demonstrations on robots have used optic flow for autonomous hovering using a down-ward facing camera [20]. Some have tried to extend this work to include position- and velocity- control with limited results, and they don't explain the wide-range of bee capabilities using optic flow [21-22].

Several groups have tried to more accurately represent these bee mechanisms rather than just generating bio-inspired algorithms. Franceschini's optic-flow regulator model is shown to control vertical lift of a micro helicopter by regulating the ventral optic flow, displaying remarkably similar behavior to insects in landing, maintaining altitude, and headwind flight phases [23]. Related further work has extended the autopilot and explained how optic flow can be regulated the same way in the lateral, ventral and dorsal planes by modelling the movement and control of a bee in a tunnel through simulation [24-25]. Some authors have gone on to test this on a hovercraft in corridors [26]. While the control methods developed in this work have been verified and adequately explained navigation in bees, further study needs to be done. The most comprehensive control methods have not been experimentally validated [24-25], and those that have are limited to simple, constrained robots [26]. Ground robots do not experience the same flight constraints, magnitude of optic flow values, and variations in the optic flow field as flying insects, because their rotation is limited to yaw corrections, and thus, they do not experience rolling and pitching.

While the basic control scheme is generally accepted to be sound, very limited work has been done to verify this navigation scheme on a flying vehicle. Conroy et al. has developed a method for accurately representing visual cues to facilitate corridor navigation for a flying robot (specifically, a quadcopter) [27]. The focus in this work was the implementation of wide-field integration of optic flow and the aforementioned analysis using a slightly modified version of the generally accepted control method showing good results. However like most work [21-23, 26-27], the methods verify only some of the behaviors of bees in corridors (here, lateral control) but not all. The lack of robust development on flying vehicles motivates additional study.

The goal of this research is to further develop and verify visual navigation for a sUAV based on honeybee control mechanisms. Experimental tests show instability of the generally accepted control and that it needs modification to demonstrate the desired behavior. This work extends adapts the control and analyzes with experimental testing on a sUAV that tests the altitude, lateral, and velocity control. A quadcopter is chosen as an experimental platform for its simple mechanical control and its similarity to a honeybee in terms of flight capabilities, degrees-of-freedom, and constraints. It also has similar flight modes (e.g. hover, cruise, VTOL, etc.). This similarity means it will also experience similar optic flow fields (unlike ground robots). The control methodology is modified to support navigation for flying vehicles (and therefore, flying insects) and tested and analyzed experimentally in variations of the benchmark corridor/hallway navigation task which is commonly used in behavioral experiments with bees.

III. Problem Formulation

The benchmark hallway navigation task is used to formulate the reactive control problem here. While true insect navigation is considerably more complex, optic flow control is commonly evaluated and demonstrated by the ability to navigate in corridors as discussed previously. Therefore, variations on this scenario were used to develop and test the entire bio-inspired approach using a quadcopter UAV.

A. Problem Definition

The navigation task is formulated as depicted in Figure 3 below where the hallway and environment are all fixed. The quadcopter (or bee) travels forward through the hallway and uses visual cues to result in centering behavior. This forward navigation represents a single flight mode of the quadcopter where landing, hover, take-off, etc. are other possible modes. As more work has been done on using optic flow to achieve these simpler tasks, the focus of this work is on this more complicated scenario. Therefore, the challenge is to explain navigation when bees are in “cruise” flight mode, and therefore, that mode is used for formulation, methodology development, and testing.

As shown above in Figure 1, the navigation planner provides high-level commands while the reactive planner is in charge of solving this low-level task (cruise). The reactive navigation problem becomes how to achieve centering performance while maintaining altitude and a fixed forward velocity given a heading direction (here, the heading is down the corridor).

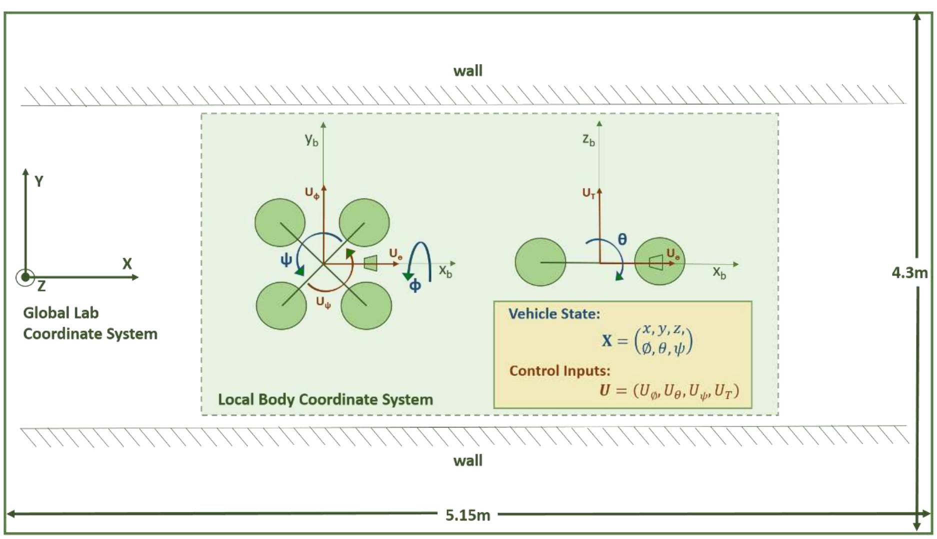

Figure 3: Problem Formulation of a Quadcopter in Hallway Benchmark Test

This is formulated similar to bee navigation where the quadcopter is oriented so the camera is front-facing. Therefore, the quadcopter uses its roll and pitch commands ($U_{\emptyset}$ and U_{θ}, respectively) to control forward velocity and lateral position in the hallway. The control methodology must then also regulate altitude and use the desired heading direction to calculate yaw and thrust commands (U_{ψ} and U_T, respectively).

B. Motion Detection

In this problem, motion detection is calculated from visual camera data supplied by the quadcopter. Since the environment is static, all optic flow detected by the quadcopter is a result of egomotion. It is assumed that the quadcopter has both a front-facing and downward-facing camera to provide information about the scene in each of the frontal and ventral fields. Bees have access to this information from their nearly panoramic field-of-view due to their compound eyes [4]. Optic flow calculations can then be done off-board using a computer vision algorithm.

Optic Flow is defined as the apparent motion of brightness patterns. Methods for computing optic flow can be classified in two main groups: sparse and dense. The Lucas-Kanade method [28] is a commonly used sparse method. It operates by identifying points of interest within an image, and tracking the movement of these points between frames. A pyramidal system is used to remove small motions and allow larger spatial movements to be tracked [29]. The main benefit of sparse algorithms is that they are less computationally demanding as they only analyze relevant parts of an image, but they can suffer from a loss of detail for larger movements as tracked points may move out of the identified area of interest. A common dense optic flow algorithm is the Farneback method [30]. This method approximates neighborhoods of two consecutive image frames by quadratic polynomials, and estimates displacement by looking at how the polynomial transforms between frames. The algorithm gives lower errors than Lucas-Kanade but at higher computational cost.

The mathematical limitations of 3D information extraction from optic flow data have been thoroughly investigated. Koenderink approached this by imagining an optimal algorithm, and concluded that the major source of error comes from the optic observations themselves [31]. It was found that the error in the predicted scene direction of motion is inversely proportional to the width of field-of-view. This stresses the need for good equipment to generate visual data to feed into the optic flow algorithm.

Optic flow was derived using the Farneback optic flow function described. Similar to many optic flow algorithms, Farneback uses a pyramidal approach where displacement is obtained by looking at flow over successively smaller windows. This is motivated by the fact that prior iterations of the algorithm required the motion field to be temporally consistent which would cause issues with high frequency noise generated by the flying quadcopter [30]. The function first converts all images to greyscale and then works on two successive image frames to determine the flow field around the robot. This is done by first approximating neighborhoods of pixels by quadratic polynomials and then looking at how the quadratics transform between the frames which gives an estimation of displacement.

Using the resultant values, the optic flow purely due to translation can be obtained. The displacement in each pixel is approximated by Equations (1) and (2) below using the angular velocities ($\omega_{roll}, \omega_{pitch}, \omega_{yaw}$), linear velocities ($T_x, T_y, T_z$), and camera focal length (f) [30]. From these equations, the optic flow only due to rotation can be estimated using feedback from the gyroscope. This can then be subtracted from the total flow field to receive purely translational flow.

$$u' = u + f * \omega_{roll} - y * \omega_{yaw} + \frac{x^2 * \omega_{roll}}{f} - \frac{x * y * \omega_{pitch}}{f} + f\frac{T_x}{Z} - u\frac{T_z}{Z} \tag{1}$$

$$v' = v - f * \omega_{pitch} + x * \omega_{yaw} - \frac{y^2 * \omega_{pitch}}{f} + \frac{x * y * \omega_{roll}}{f} + f\frac{T_y}{Z} - v\frac{T_z}{Z} \tag{2}$$

$$x, y = pixel\ coordinate\ from\ centre\ of\ frame$$

IV. Methodology

The control methodology proposed here is a bio-inspired technique built around the ability of bees to use optic flow feedback to navigate during cruise flight mode. Again, the control is developed for a quadcopter sUAV as it can emulate biological capabilities. The control scheme, optic flow calculations, and filtering method are described here.

A. Control Scheme

The control scheme developed is based on the reactive flight control of bees and the interaction with a higher-level, active navigation planner (Figure 4). The navigation planner provides information about desired directional heading and flight mode selection to the reactive control scheme. While bees make reactive changes to their heading, the yaw control is mainly governed by a higher-level planner. Therefore, the desired heading is assumed fixed.

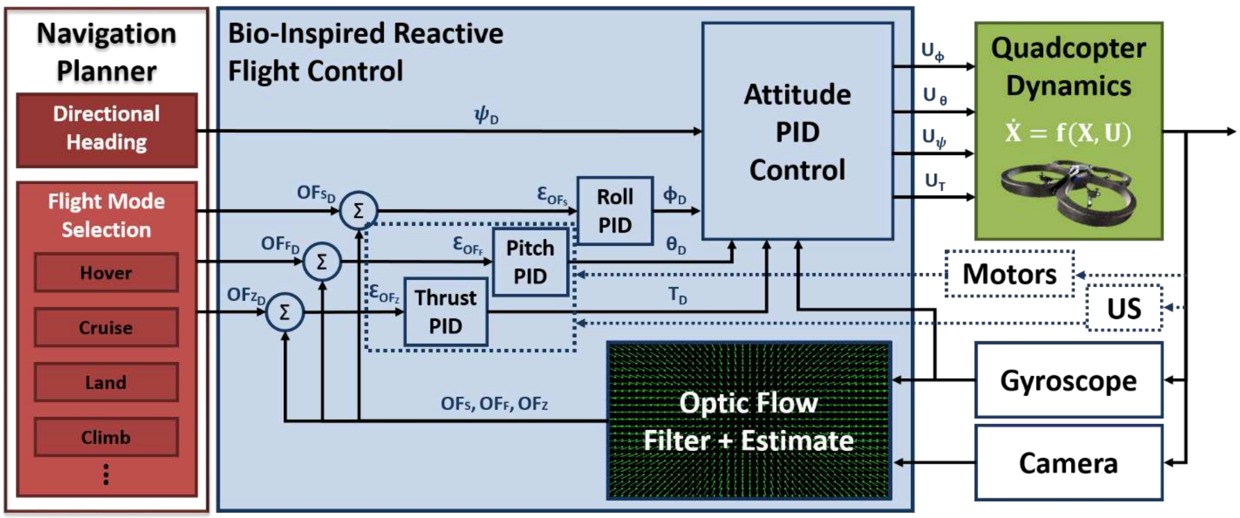

Figure 4: Bio-Inspired Reactive Flight Control Scheme

The reactive control scheme then regulates the desired roll, pitch, and altitude using optic flow cues where the maximum desired roll and pitch are 5° (~0.5 m/s) and 20° (~2 m/s), respectively. Similar to heading, the "desired" optic flow setpoints come from the high-level navigation planner and are dependent on the flight mode selection. The setpoint for the forward optic flow (OF_{F_D}) governs the forward velocity, the side optic flow setpoint (OF_{S_D}) governs the lateral position in the tunnel, and the setpoint for ventral optic flow (OF_{Z_D}) governs the altitude. As the cruise flight mode during navigation in a hallway is the focus of this work, those calculations are described here below. However, it is easy to see how these would be adapted for different flight modes. For example, the forward optic flow setpoint (OF_{F_D}) would be equal to 0 for hover but set to an empirical value for cruise.

Given the setpoints from the high-level planner, the control scheme uses PID control to minimize the error between the desired and actual values of optic flow. The feedback come from the camera optic flow calculations that are then fed into a filter which estimates the actual values (discussed further below). The errors in the side, forward, and ventral optic flow values (OF_{S_D}, OF_{F_D}, and OF_{Z_D}) with the PID control can then be used to calculate a desired roll, pitch, and thrust ($\emptyset_D$, θ_D, and T_D), respectively. These values along with the desired heading are used by the attitude PID control to send motor commands to the quadcopter.

The generally accepted control scheme discussed in previous work is not suitable to achieve reliable hallway navigation. This is due to the fact that at low forward velocity and transitional periods, the optic flow values vary widely, and instabilities cause the control to fail. Therefore, an alteration to the altitude and forward control method is proposed. In Figure 4 above, the dashed boxes and lines represent where the scheme was altered from the original and depict the additional feedback used (motor speed sensors and ultrasound here). The adapted control is expanded on below in Figure 5 where the dashed lines correspond to the alterations made to the original scheme

Instead of velocity being directly regulated, optic flow is used to generate a desired forward velocity (V_D). The corresponding error ($\mathcal{E}_V$) is calculated using additional sensing data to estimate the actual velocity ($\tilde{V}$) and is then inputted into the PID control to produce the desired pitch. Similarly, the attitude is regulated using additional feedback from an ultrasonic sensor. This results in the same behavior as regulating forward velocity according to total optic flow (or altitude using ventral optic flow) but does so indirectly.

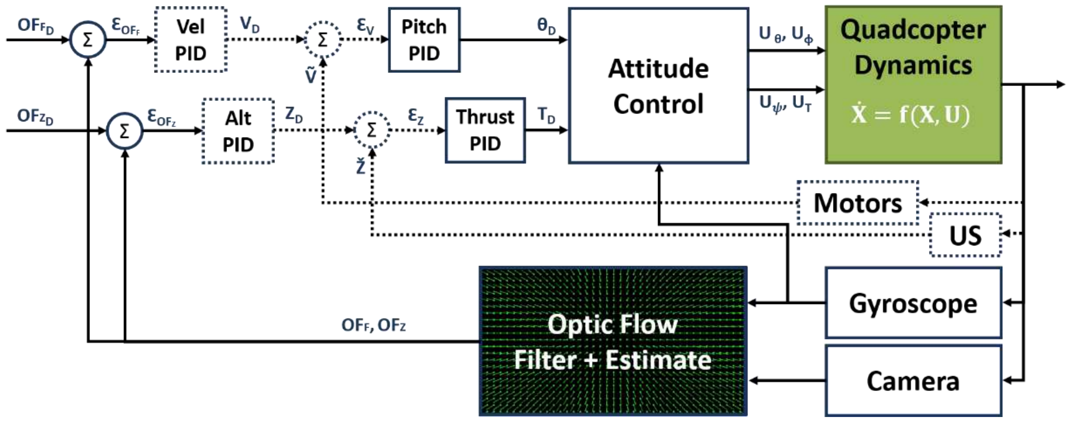

Figure 5: Adapted Method from General Optic Flow Control Scheme

B. Optic Flow Calculations

Again, the values of the desired optic flow setpoints are dependent on the flight mode selection, come from the higher-level planner, and are fixed from the viewpoint of the reactive control system. Depending on the flight mode, the calculations of the actual optic flow values vary. As the focus is on cruise, this is what is expanded on below (though the same concepts behind the calculations can easily be applied to other modes).

Evidence shows that bees maintain a forward velocity by fixing the summation of the optic flow across the entire visual field to an empirical value and that this value is about 300 degrees/s [4]. This same method is used here to calculate a desired pitch with the exception that we vary the setpoint to achieve various maximum velocities. As translational optic flow in the x-direction is a better indicator in forward motion, this is used to calculate the actual forward optic flow (OF_F) as shown below in Equation (3). It is also important to note that during forward motion this flow in the left half of the visual field will be negative (and the right half, positive) which needs to be accounted for.

$$\mathrm{OF}_F = \sum_{x<0} -u' + \sum_{x\geq 0} u' \tag{3}$$

During normal cruise conditions, the desired roll is set to 0 for stable flight. The quadcopter can achieve this by balancing the optic flow in the left and right halves of the visual field. More realistically, the bee is probably balancing either the left or right optic flow against an empirical setpoint similar to above as this would also explain the wall-following behavior which is common in bees. Therefore, this method is used as shown in Equation (4).

$$\mathrm{OF}_S = \mathrm{argmax}\left[\left(\sum_{x<0} -u'\right), \left(\sum_{x\geq 0} u'\right)\right] \tag{4}$$

Finally, altitude regulation is achieved similarly. However instead, the optic flow is determined using the downward facing camera, and therefore, large changes in the y-direction of optic flow are indicative of a closer distance to the ground when at a fixed velocity. This means altitude can be regulated using another empirical setpoint corresponding to the desired altitude and Equation (5) below.

$$\mathrm{OF}_Z = \sum_{y} -v' \tag{5}$$

C. Filter

Due to large variations in the optic flow field, a moving average filter was implemented on the actual values before inputting into the control system. Here, an Exponential Moving Average (EMA) was used with a long time constant to adjust for the large variations in flow. The EMA is a type of Finite Impulse Response (FIR) filter that is widely-used to filter out noise from random fluctuations by weighing newer data points more heavily [32]. The optic flow exponential moving average (OF_EMA_i) uses a smoothing parameter between 0 and 1 (α) that represents the degree of weighting of a new data point (OF_i) as shown below in Equation (6). The smoothing parameter is then tuned such that it filters unwanted fluctuations but actually represents the underlying curve.

$$\mathrm{OF\_EMA}_i = \alpha \cdot OF_i + (1-\alpha) \cdot \mathrm{OF\_EMA}_{i-1} \tag{6}$$

V. Testing and Results

As discussed, this methodology is tested and verified experimentally using the benchmark hallway navigation task. A total of 3 tests were completed to verify the various components of the control scheme. The results show information about position, optic flow, and velocity as the quadcopter travels down the hallway. This section describes the setup, gives results, and discusses the outcomes.

A. Experimental Setup

For this task, a commercially-available AR Parrot Drone 2.0 [33] was used as a testbed, because they are inexpensive and have been widely used for independent projects. Due to this, there is a fair amount of support in forums so a lot of issues like setting up communication and sending wireless commands have already been solved [34]. The AR Parrot Drone is fitted with a front-facing HD and downward-facing QVGA camera which are both used for optic flow calculations and is depicted below in Figure 6. The structure is made of carbon fiber tubes, making it very lightweight, and comes with both an indoor and outdoor hull. Additionally, it has 4 brushless motors that can be reprogrammed for full control. The system has built-in stabilization, 8-10 minutes of flying-time battery life, and 165-meter range and 50-meter height.

The lab was configured with two walls along the length (fitted with generic graphics well suited for the drone camera and optic flow algorithm) and a motion tracking system providing ground truth data (Figure 6). Sensor data from the drone was sent over Wi-Fi to an off-board workstation where feedback is processed and control commands are computed.

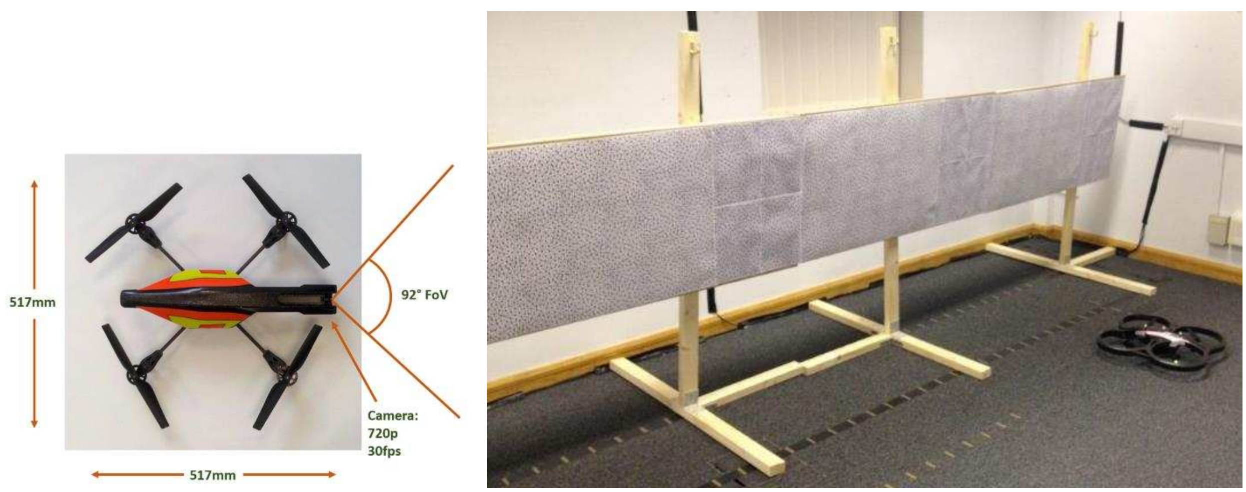

Figure 6: Experimental Setup: Depiction of AR Drone Quadcopter and Lab Configuration

B. Testing Results

As shown in the following results, trying to tune and control the desired roll, pitch, and thrust ($\emptyset_D$, θ_D, and T_D) simultaneously using optic flow is incredibly difficult. A large contributing factor is the fact that the magnitude of the optic flow values are very dependent on the forward velocity, and so if the velocity is inconsistent, results can be mixed. Therefore, the tests were broken down such that precise motion tracking data was used in the tests to fix 1 or 2 control modes so as to test the ability of the optic flow control in the other mode/s. This was completed using 3 tests with 10 trails each as follows:

Test #1: Verification of roll control using lateral optic flow balancing. Altitude and pitch are fixed and controlled using precise feedback.

Test #2: Verification of altitude control using ground optic flow balancing. Roll and pitch are fixed and controlled using precise feedback.

Test #3: Verification of simultaneous roll and pitch control using lateral and forward optic flow balancing. Altitude is fixed and controlled using precise feedback.

Test #1

Test #1 was completed to verify the roll control using lateral optic flow balancing while altitude and pitch were fixed and controlled using precise feedback. With this, the ability to regulating the lateral degree-of-freedom could be isolated. This allowed for the analysis of the proposed approach before adding the complexity of also regulating the forward and altitude degrees-of-freedom using optic flow. Figure 7 below shows the results of the path traversed and the mean path over the trial runs.

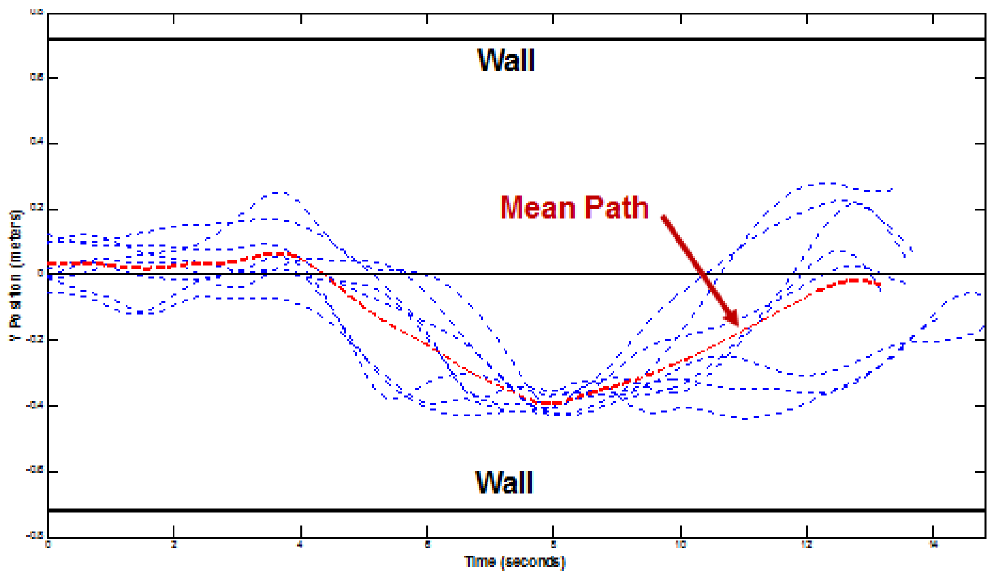

Figure 7: Path Traversed by Quadcopter in Hallway Navigation Test #1

The results above show suitable performance at centering over the length of the tests. While there were some oscillations, it is expected that these would dampen out over a longer trial run and is also consistent with honeybee experiments [18]. Furthermore, the deviation from the centerline was consistent over the trials indicating that the control method is sound and that there was some object/s causing a large increase in optic flow in the left visual field.

This was further verified by looking at the optic flow, wall-distance (from left wall), and velocity over a single trial as shown below in Figure 8. It can be seen that the left optic flow is quite large compared to the right even though the quadcopter is in the center of the hallway. However, this verifies the control method as this would naturally produce a roll and change of position to the right (as is shown). When the quadcopter gets too close to the right wall, the optic flow values in the right field sharply increase which produces the desired effect of a roll to the left. While the lateral control is confirmed, it can be seen that even small variations in velocity cause large variations in optic flow.

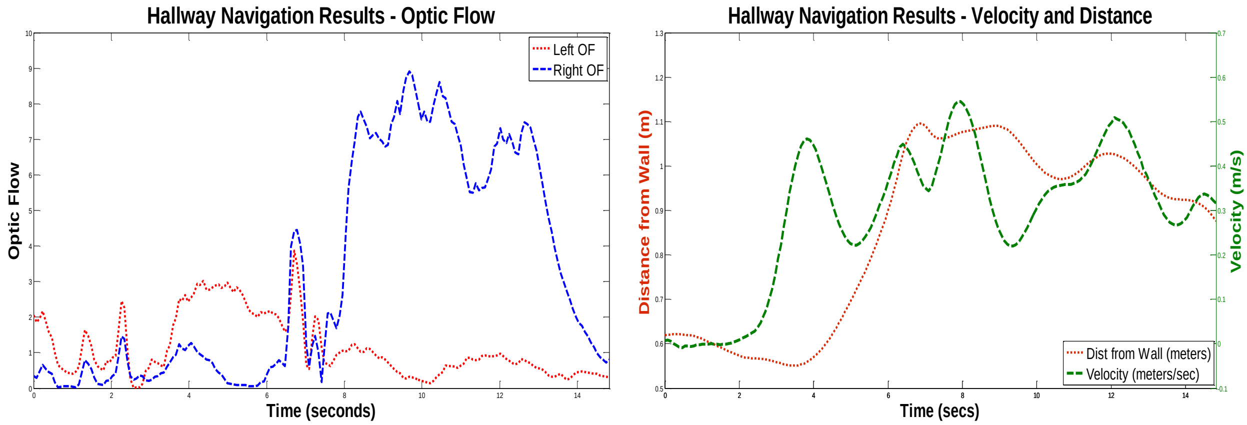

Figure 8: Test #1 Example Trial Depicting Optic Flow, Distance from Wall, and Velocity Data

Test #2

Test #2 was completed to verify the altitude control using ground optic flow balancing while roll and pitch were fixed and controlled using precise feedback. With this, the altitude control could be isolated. Figure 9 below shows the results of the path traversed and the mean path over the trial runs. The thin black line represents the altitude which would correspond to the desired OF altitude setpoint (OF_{Z_D}) under the experimental conditions.

It can be seen that the performance is reasonable over individual trials and that the overall average performance is very good with little overshoot, few oscillations, and quick return to the desired altitude. The results also are especially good in that they did not result in instabilities over any individual trial whereas the method using optic flow to directly regulate altitude did almost every trial (not shown).

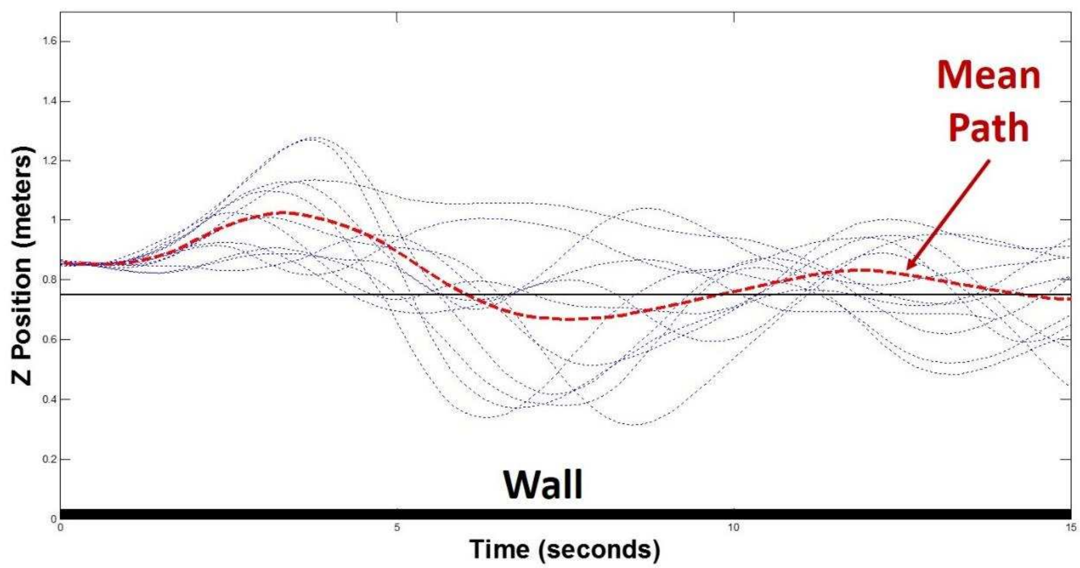

Figure 9: Path Traversed by Quadcopter in Hallway Navigation Test #2

The results are further studied by looking at the optic flow, wall-distance (same as altitude in this test), and velocity over a single trial as shown below in Figure 10. Despite the first few seconds where it sharply increases, the forward velocity is very consistent. During this period where variations in velocity are minor (t>4s), the relationship between the wall distance and optic flow is clearer. That is, the optic flow increases as the distance to the wall decreases. This reinforces the proposed control scheme. However, this trial also perfectly highlights the need for further investigation and where the more general control scheme fails. During the transitional period where velocity varies quickly, the optic flow values are low even though the distance to the wall is small and velocity is increasing. This is where an instability would occur for the general method but where the adapted control method produces the desired result.

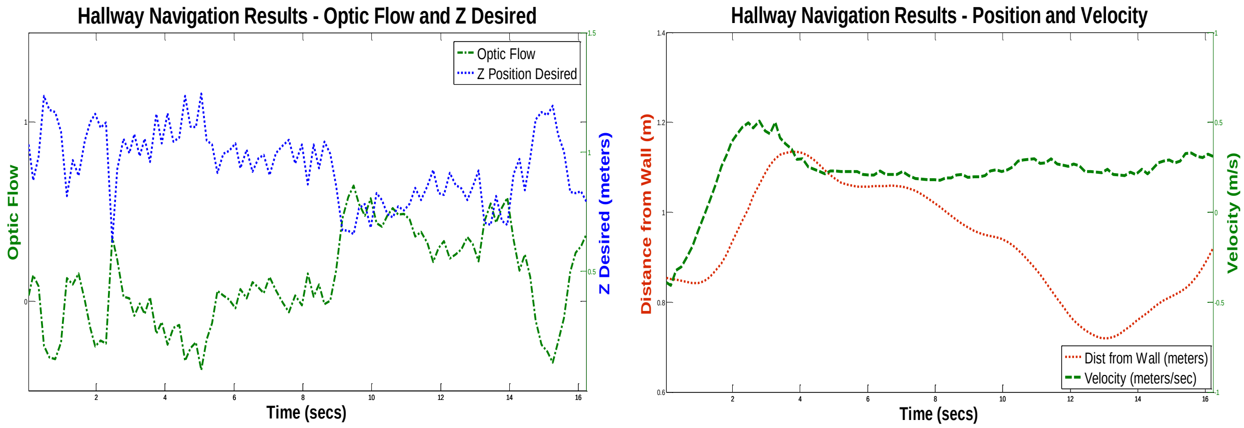

Figure 10: Test #2 Example Trial Depicting Optic Flow, Desired Z Position, Distance from Wall, and Velocity Data

Test #3

While the optic flow control scheme can be verified by regulating a single control mode at a time as above, it becomes much more difficult once trying to control them simultaneously. This is due to the natural, large variations in the flow field from regular quadcopter motion. Test #3 was completed to control roll and pitch simultaneously using lateral and forward optic flow balancing while the altitude was fixed and controlled using motion tracking feedback. This test verifies that controlling multiple modes using the optic flow reactive scheme is possible, but it also highlights the subtleties, and therefore difficulties, of using this method. It also further verifies and reinforces the use of the adapted control scheme.

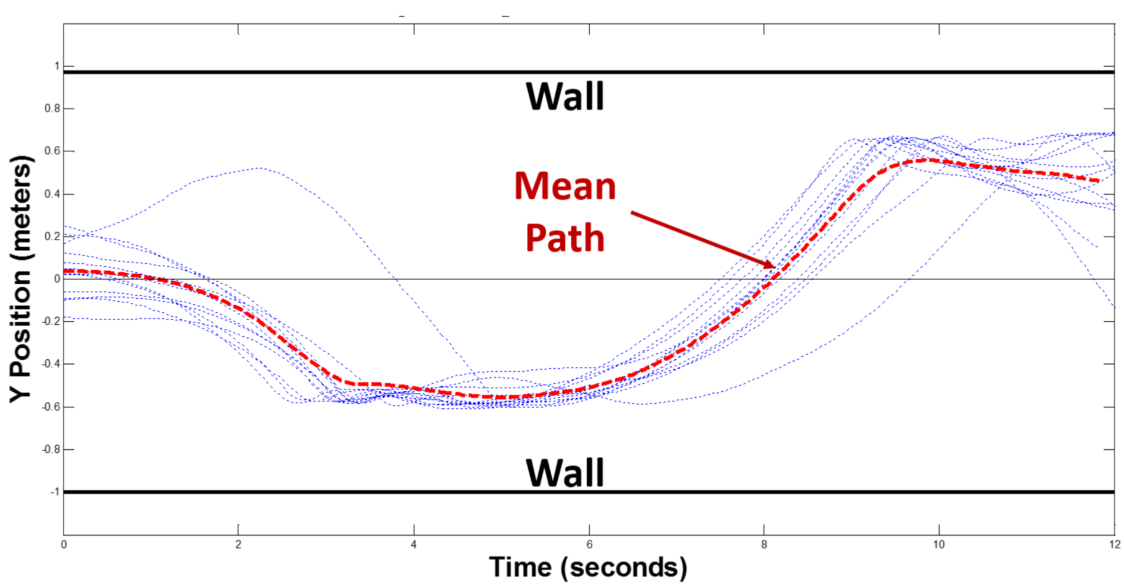

Figure 11: Path Traversed by Quadcopter in Hallway Navigation Test #3

Similar to Test #1, the results in Figure 11 above show suitable performance at centering over the length of the tests. Again, there were some oscillations that would be expected to dampen out over time. This test further verifies the lateral control method as it was completed while also regulating forward velocity.

The results can be further analyzed by looking at the optic flow, wall-distance (from left wall), and velocity over a single trial as shown below in Figure 12. Left and right optic flow values are as expected as the distance from the wall varies. Additionally, the forward velocity is regulated according to the changes in total optic flow producing the desired velocity regulation effect. However, there were large variations in forward velocity still. It is possible this would settle out over time, but it highlights the challenges and underwhelming performance at low velocities.

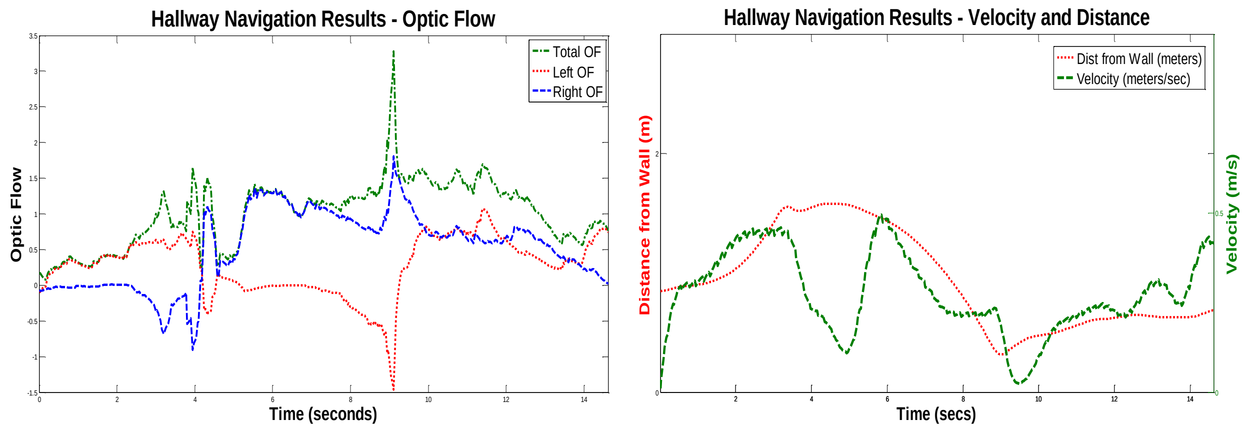

Figure 12: Test #3 Example Trial Depicting Optic Flow, Distance from Wall, and Velocity Data

C. Discussion
While the control scheme is verified in these tests, an adapted method had to be adopted to stabilize the system using additional feedback. The adapted method shows good results and is consistent with observed behavioral experiments in biology. It is possible this also has biological relevance as bees could have estimates of forward speed and altitude from other sensory input (e.g. muscle feedback, sensilla, etc.) though this needs further study.

However, the results could be significantly improved. The methodology certainly explains the underlying mechanisms but unfortunately, not all of the behavior. The main challenge comes from the large variations in the optic flow due to artifacts in the visual field, corrections made by the quadcopter, and errors from the optic flow algorithm. This makes the algorithm not very effective at low forward speeds (<0.5m/s) as noise and rotational flow can overpower navigation cues. While some of this is due to the consequence of implementation on robots, the rest is not unique to robots and implies that bees are performing a much more complex algorithm than previously thought.

VI. Conclusions
UAVs are being increasingly used to perform missions that are either too boring, unsafe, or undesirable for humans. A large subset of this growing industry is small UAVs (sUAVs) which are more agile and require only a single operator, but traditional guidance systems for UAVs are not always suitable for a transition to sUAVs. State-of-the-art guidance for UAVs typically rely on high-quality GPS and Inertial Measurement Units (IMUs). However, these are not always available when flying indoors or for small, lightweight UAVs where power is limited and sUAVs must make careful decisions about how to best utilize that power.

Traditional control techniques for UAVs tend to be insufficient as they fail in the face of dynamic and uncertain environments. New navigation techniques for sUAVs are motivated by the performance of small insects and the lack of current reliable methods. In this research, a bio-inspired control method using vision-based optic flow is motivated by bee navigation in hallways. The results show an adapted method both explains behavioral results and achieves stability despite large variations in feedback. Furthermore, this work represents one of very few that has been done to try to go on and verify the method on a flying vehicle.

More complete study is needed in the area of the optic flow from different optic flow algorithms themselves, over various visual inputs, from corrections made by the flying robot, and filtering methods. The Green Brain Project is investigating the area of bee visual processing by modelling the regions of the brain in charge of optic flow calculations as little is currently known from a biological viewpoint [35]. With this, the control method can be improved and include the subtleties that this method requires. This would also allow for further simulated study of the control methods under variations in parameters. Ultimately, this might allow for the benefits that this method permits like automatic altitude and speed regulation when in proximity to terrain or obstacles and navigating narrow corridors. Furthermore, this scheme would also explain and permit obstacle avoidance.

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References

1. S. Tsach, A. Peled, D. Penn, B. Keshales, and R. Guedj, "Development Trends for Next Generation UAV Systems," AIAA Infotech@Aerospace Conference and Exhibit, California, AIAA 2007-2762, 2007.
2. "Air Vehicles Vision 2009," Air Vehicles Directorate, Air Force Research Laboratory, 2009.
3. M. Srinivasan, "Honeybees as a Model for the Study of Visually Guided Flight, Navigation, and Biologically Inspired Robotics," Physiological Reviews, Vol. 91, No. 2, pp. 413-460, 2011.
4. M. Bitterman, R. Menzel, A. Fietz, and S. Schaefer, "Classical Conditioning of Proboscis Extension in Honeybees," Journal of Comparative Psychology, Vol. 97, Issue 2, pp. 107-119, 1983.
5. H.E. Esch, S Zhang, M.V. Srinivasan, and J. Tautz, "Honeybee Dances Communicate Distance Measured by Optic Flow," Nature, Vol. 411, 2001.
6. A. Barron and M. Srinivasan, "Visual Regulation of Ground Speed and Headwind Compensation in Freely Flying Honey Bees," Journal of Experimental Biology, Vol. 209, Issue 5, pp. 978-984, 2006.
7. M.V. Srinivasan, S.W. Zhang, J.S. Chahl, E. Barth, and E. Venkatesh, "How Honeybees make Grazing Landings on Flat Surfaces," Biological Cybernetics, Vol. 83, Issue 3, pp. 171-183, 2000.
8. J. Zufferey, "Bio-Inspired Vision-Based Flying Robots," Ph.D. Thesis, EPFL: Ecole Polytechnique Federale De Lausanne, 2005.
9. J.C. Sandoz, "Behavioral and Neurophysiological Study of Olfactory Perception and Learning in Honeybees," Frontiers in Systems Neuroscience, Vol. 5, Article 98, 2011.
10. J. Reinhard, M. Srinivasan, and S Zhang, "Olfaction: Scent-triggered navigation in honeybees," Nature Brief Communications, Vol. 427, pp. 411, 2004.
11. M.V. Srinivasan, M. Poteserb, and K. Kralb, "Motion Detection in Insect Orientation and Navigation," Vision Research, Vol. 39, No. 16, pp. 2749–2766, 1999.
12. F.C. Dyer and J.A. Dickinson, "Sun-Compass Learning in Insects: Representation in a Simple Mind," Current Directions in Psychological Science, Vol. 5, No. 3, pp. 67-72, 1996.
13. G. Nalbach, "The Halteres of the Blowfly Calliphora: I. Kinematics and Dynamics," Journal of Comparative Physiology A, Vol. 173, No. 3, pp. 293–300, 1993.
14. R. Dudley, "The Biomechanics of Insect Flight: Form, Function, Evolution," Princeton University Press, NJ, 2000.
15. A. Sherman and M. H. Dickinson, "Summation of Visual and Mechanosensory Feedback in Drosophila Flight Control," Journal of Experimental Biology, Vol. 207, pp. 133–142, 2004.
16. D. Floreano and R. Wood, "Science, Technology and the Future of Small Autonomous Drones," Nature, Vol. 521, pp. 460-466, 2015.

17. P.G. Mobbs, "The Brain of the Honeybee Apis Mellifera. I. The Connections and Spatial Organization of the Mushroom Bodies," Philosophical Transactions B, Vol. 298, pp. 309-354, 1982.
18. W.H. Kirchner and M.V. Srinivasan, "Freely Flying Honeybees use Image Motion to Estimate Object Distance," Naturwissenschaften, Vol. 76, No. 6, pp. 281-282, 1989.
19. M.V. Srinivasan, M. Lehrer, W.H. Kirchner, and S.W. Zhang, "Range Perception through Apparent Image Speed in Freely Flying Honeybees," Visual Neuroscience, Vol. 6, No. 05, pp. 519-535, 1991.
20. A. J. Cope, P. Richmond, J. Marshall, and D. Allerton, "Creating and Simulating Neural Networks in the Honeybee Brain using a Graphical Toolchain," Society for Neuroscience Meeting, Program No. 678.12, 2013.
21. F. Kendoul, I. Fantoni, and K. Nonami, "Optic Flow-Based Vision System for Autonomous 3D Localization and Control of Small Aerial Vehicles," Robotics and Autonomous Systems, Vol. 57, No. 6-7, pp. 591-602, 2009.
22. N. Gageik, M. Strohmeier, and S. Montenegro, "An Autonomous UAV with an Optical Flow Sensor for Positioning and Navigation" International Journal of Advanced Robotic Systems, Vol. 10, 2013
23. N. Franceschini, F. Ruffier and J. Serres, "A Bio-Inspired Flying Robot Sheds Light on Insect Piloting Abilities," Current Biology, Vol. 17, pp. 329-335, 2007.
24. G. Portelli, F. Ruffier, F. Roubieu and N. Franceschini, "Honeybees' Speed Depends on Dorsal as well as Lateral, Ventral and Frontal Optic Flows," PLoS One, Vol. 6, No. 5, 2011.
25. G. Portelli, J. Serres, F. Ruffier, and N. Franceschini, "Modelling Honeybee Visual Guidance in a 3-D Environment" Journal of Physiology – Paris, Vol. 104, No. 1-2, pp. 27–39, 2010.
26. F.L. Roubieu, J.R. Serres, F. Colonnier, N. Franceschini, S. Viollet, and F. Ruffier, "A Biomimetic Vision-Based Hovercraft Accounts for Bees' Complex Behaviour in Various Corridors," Bioinspiration and Biomimetics, Vol. 9, 2014.
27. J. Conroy, G. Gremillion, B. Ranganathan, and J. S. Humbert, "Implementation of Wide-Field Integration of Optic Flow for Autonomous Quadrotor Navigation," Autonomous Robots, Vol. 27, No. 3, pp. 189-198, 2009.
28. B. D. Lucas and T. Kanade, "An Iterative Image Registration Technique with an Application to Stereo Vision," International Joint Conference on Artificial Intelligence, Vol. 2, pp. 674-479, Vancouver, 1981.
29. G. Bradski and A. Kaehler, "Optic Flow," Learning OpenCV, O'Reilly Media, pp. 322-337, 2008.
30. G. Farneback, "Two-Frame Motion Estimation Based on Polynomial Expansion," Lecture Notes in Computer Science, Vol. 2749, pp. 363-370, 2003.
31. J.J. Koenderink and A. J. van Doorn, "Facts on Optic Flow," Biological Cybernetics, Vol. 56, No. 4, pp. 247-254, 1987.
32. A.J. Lawrance and P.A.W. Lewis, "An Exponential Moving-Average Sequence and Point," Journal of Applied Probability, Vol. 14, No. 1, pp. 98-113, 1977.
33. Parrot AR Drone 2.0, 2012. http://ardrone2.parrot.com/
34. DIY Drones, 2012. http://diydrones.com/
35. A. Cope, C. Sabo, K. Gurney, E. Vasilaki, and J.R. Marshall, "A Model for an Angular Velocity-Tuned Motion Detector Accounting for Deviations in the Corridor-Centering Response of the Bee," PLOS Computational Biology, Submitted, 2015.