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An Inexpensive Flying Robot Design for Embodied Robotics Research

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***Abstract* — Flying insects are capable of a wide-range of flight and cognitive behaviors which are not currently understood. The replication of these capabilities is of interest to miniaturized robotics, because they share similar size, weight, and energy constraints. Currently, embodiment of insect behavior is primarily done on ground robots which utilize simplistic sensors and have different constraints to flying insects. This limits how much progress can be made on understanding how biological systems fundamentally work. To address this gap, we have developed an inexpensive robotic solution in the form of a quadcopter aptly named BeeBot. Our work shows that BeeBot can support the necessary payload to replicate the sensing capabilities which are vital to bees' flight navigation, including chemical sensing and a wide visual field-of-view. BeeBot is controlled wirelessly in order to process this sensor data off-board; for example, in neural networks. Our results demonstrate the suitability of the proposed approach for further study of the development of navigation algorithms and of embodiment of insect cognition.**

***Index Terms*— Embodiment; Insects; Honeybees; Robotics; Quadcopters**

I. Introduction

The study of flying insects is interesting from the point-of-view of small robot and Unmanned Aerial Vehicle (UAV) design, because they share small size, low weight, and low energy consumption. 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. Recent studies with bees show they can estimate flight duration, regulate flight speed, and land using visual processing [1-3]. Beyond having the same impressive flying skills as other flying insects, honeybees achieve cognitively sophisticated behaviors despite the very limited size of their brain (approximately 10^6 neurons) [4]. A well-known example of this is the waggle dance [5]. Additionally, among other advanced cognitive abilities, honeybees have been found capable of speed-accuracy trade-offs in individual decision-making, positive, and negative reinforcement learning, contextual learning, learning advanced concepts such as 'same' and 'different', and transferring concepts across sensory modalities [6-9].

There has been extensive research into enabling small UAVs (sUAVs) and robots with similar capabilities and with comparable efficiency as flying insects as current technology is still limited [10]. This is largely due to the fact that the complications of flight for air vehicles are especially compounded for their smaller counterparts. For example, sUAVs are more likely to operate on 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 the 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, 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 sensors. Enabling sUAVs with insect-like capabilities would be a significant step-forward in state-of-the-art.

In recent years, neural networks and deep learning have overcome huge challenges in modeling and representing large-scale sets of data. Also more recently, there has been some work to accomplish this with neural models which more accurately represent the processing and dynamics in the nervous system. For example, the "Blue Brain Project" and the "Green Brain Project" are modelling the human and honeybee brain respectively, using biologically-based neural models [11-12]. The 'Green Brain' Project is addressing the gap in our understanding of cognition by building a model of the honeybee brain and embodying it within a flying robot. The aim is to describe detection, classification, and learning in the olfactory and optic pathways as well as multi-sensory integration across these sensory modalities. This project presents some state-of-the-art tools for easy creation [13], implementation [14-15], and real-time control of neural models.

In order to fully understand navigational and cognitive behaviors, it is important to understand how they are embedded in their bodies and how their bodies interact with the world. By using robots for embodiment, we can better understand the underlying processes. Embodiment allows us to implement hypothesized principles and check their soundness, robustness, and scaling properties on a physical tool in a real environment. This may challenge widely accepted "facts", suggest new experiments to be carried out on bees or other insects, and raise

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new biological questions [16-18]. One of the major advantages of this approach is that robots are easy to manipulate and simple to monitor and record data from (i.e. motor commands, internal states, etc.). Beyond fundamental research, embodiment of cognitive models also can lead to the development of intelligent systems for ground and aerial robots of practical use [19].

As such, there is a need to develop efficient and robust algorithms (e.g. neural networks) based on flying insects and the corresponding robotic platforms which enable this development. Therefore, the goal of the work was to advance robotic embodiment by designing a flying robot that can replicate honeybee sensing and behavior. A sUAV of this type could then be better used for development of: insect cognition & flight behavior, UAV visual flight-control, multi-modal flight control algorithms, and more.

In the remainder of the paper, we review relevant insect behaviors and capabilities, insect embodiment platforms, and sUAV platforms (Section II). We describe the design requirements as motivated by current state-of-the-art (Section III). We present the final robot design and methodology (Section IV). We show results and give examples of how this can be used in neural computations (Section V), and then discuss the significance of our findings and future work (Section VI and VII, respectively).

II. Background

A. *Flying Insect Sensing and Behavior*

The visual and olfactory systems in insects are implicated in complex cognitive behaviors which are not currently understood. They are of interest to robotic applications as they are shown to be essential to biological autonomous agents.

1) *Vision*

There has been extensive research in recent years into honeybee vision and flight navigation as bees are known to have impressive capabilities. For example, honeybees will seek out food over 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. It has been shown that bees use their visual system to regulate their velocity in flight, control their course, estimate distance travelled through path integration, avoid obstacles, and land smoothly [10]. Bees are able to accomplish these tasks, because they use Elementary Motion Detectors (EMDs) to discern Optic Flow (OF). While this aspect of honeybee vision is fairly well understood, little else is known about the honeybee visual system.

Like the majority of insects, honeybees have two compound eyes that each contain ~5500 ommatidia. Each ommatidium has a lens that detects light covering a small angle and each from a different direction. The light is focused onto 3 different classes of photoreceptors (ultraviolent, blue, and green sensitive) resulting in honeybee's color vision [20]. Unlike humans, these classes of photoreceptors respond at shorter wavelengths which likely helps with flower recognition and discrimination.

The spacing and acceptance angle of the ommatidia results in the large field-of-view. It is these two parameters (spacing and acceptance angles) that produce the bee's spatial resolution of the bee's eye and how much the world appears blurred. The acceptance angles allow neighboring ommatidia to view neighboring regions of space. It has been found that the ommatidia are packed more densely near the center of the eyes than at the edges. The central ommatidia have a visual angle of about 1º whereas those furthest from the center can be up to 3º [21]. Additionally, the honeybee's eye is almost four times as long as it is wide which leads them to resolve objects better vertically than horizontally [22].

Between the two eyes and ~11,000 ommatidia, the bees have a near-panoramic field-of-view with a significant binocular overlap (~30 º in the front and similar in the dorsal and ventral regions) [21]. The only thing stopping them from having a full panoramic view is where their body obstructs their vision and creates a blind spot in the back. Studies have been performed to try to determine how fast bees can actually see rapidly changing images. It has been established that bees have a temporal resolution between 165–300 Hz implying that they may resolve images up to a maximum of 300 Hz [23].

2) *Olfaction*

Honeybee olfaction plays an important role in bees' daily lives. It allows them to communicate, detect dangers, and forage on flowers as it is the primary sense used to differentiate flowers. Much of the learning that takes place in the olfactory system is associative and is based on positive and negative conditioning. Not only can they learn that individual odors might be rewarded, but they can also learn that when combined with other odors, they now might be punished (non-elemental learning) [24]. This is necessary for bees as the world is filled with mixed, complex odors where they need to constantly make decisions and select appropriate actions.

Odor detection primarily takes place on the bees' antennae. Bee antennae are covered in tiny hairs, called sensilla, which contain Olfactory Receptor Neurons (ORNs). The antennae has roughly 170 types of odor receptors which send information to so-called glomeruli in the antennal lobe, the primary olfactory processing unit. ORNs and glomeruli allow bees to be sensitive to a practically unlimited number of different odorants. After initial pre-processing in the antennal lobe, odor information gets passed to higher brain centers through projection neurons that follow two separate tracts. These two tracts have different response times and are believed to provide two separate types of information: (1) general information about the identity of the odor and (2) more specific information about where and when the odor was encountered [25]. It is likely that this parallel processing is one reason for bees' ability to distinguish scents despite the complexity of many mixed odors.

B. *Insect Behavior & Cognitive Embodiment*

Ground robots are the typical platform of choice for embodiment of insect and cognitive behaviors though some testing has been performed on aerial robots [10, 26]. This is due to their constrained motion, and so their stable, simple, and slow dynamics make control easier. They can also hold heavy payloads and operate in many diverse environments. Ground robots have demonstrated steering, distance estimation, and obstacle avoidance [27-28]. They have also been used for olfactory-related tasks in order to detect, localize, and navigate toward odor cues [29]. Rugged, wheeled robots have been taken out of the lab and utilized outdoors to replicate the path integration and landmark steering of ants [28]. Hovercrafts have been primarily used to demonstrate the corridor centering response and other reactive control tasks in a hallway [27]. While ground robots are typically used for embodiment, they are limited in their Degrees-of-Freedom (DoF) and are not subjected to the same uncertainties as flying robots. As a result, navigation algorithms for ground robots do not always translate well to aerial vehicles.

sUAVs are becoming more affordable and flexible with the development of miniaturized electronics. They also have a large open-source community which makes them a good choice for current research and development. Small UAVs can be grouped into 3 categories: fixed-wing, rotorcraft, and flapping-wing flyers. Fixed-wing and flapping-wing aerial robots have had limited applications in embodiment with some marginal success with basic OF control [19]. While fixed-wing aircraft have longer flight times and can carry a decent payload, they need to maintain a minimum velocity to generate lift and have other constraints that make agile maneuvers difficult (i.e. they require a minimum turn radius). This makes it difficult to replicate the maneuverability of insects using a fixed-wing platform.

There has been a lot of advancement in the last decade on flapping-wing technology, but these platforms still suffer from limited payload capacity and short flight times [30]. Additionally even though theoretically flapping-wing flight should be more power-efficient, technology has yet to be able to produce this same result which has led to many of these flyers needing to be tethered to maintained sufficient power.

Rotorcraft provide a good compromise between the other two categories in that they can be used to produce the same behavior as insect flight and can support a small but decent payload. The main drawback to rotorcraft is their power requirements which proportionally increases with the payload requirements. Despite their limitations, it is because of these advantages that has led to the popularization and commercialization of quadcopters and therefore, their inexpensive nature [31]. As a result, hovercraft and quadcopters have seen the widest range of application including obstacles avoidance, odometry, and lateral, ventral, and forward OF control [17, 26, 32]. However, their complex dynamics make the control problem very difficult, and most demonstrations have been on single DoFs or in very constrained environments. Further, they have seen limited chemosensing capabilities and primarily use simplistic OF sensors (rather than using visual inputs to calculate OF).

III. Design Requirements

There is a lack of flying robots that are suitable for embodiment and development of flying insect visual navigation models. As stated, neural models have shown to reproduce the robust capabilities of insects (for example, in the AVDU model in calculating OF [33]), but it is difficult to further develop and verify these models without the appropriate body in which to embed them. Simulations have difficulty duplicating the uncertainties and dynamism that insects face in real life, and so it is essential to have robotic platforms to test models in real-world conditions.

This problem is further described below with its plausible testing scenario and the subsequent design specifications. The sUAV is then evaluated on how well it meets the design requirements and on the system response.

A. *Problem Description*

As stated, there is a need for a flying robotic platform for research in embodiment that can be used in scaled testing. An aerial robotics laboratory provides a semi-controlled space which can be used to help understand biological capabilities before testing them in real-life scenarios. By first testing in a lab environment, the response to controlled stimuli can be evaluated as a precursor to examination in less constrained situations. This methodology provides a good tool for understanding embodied insect flight behavior which can be studied from pure simulation up to real-world deployment.

Indoor testing of sUAVs requires wireless communications and a moderate amount of space. Communication is more reliable indoors since distances are short but interference and noise can be moderate. This environment is also characterized by semi-controlled lighting, low ventilation, uncontrolled airflow, and unknown odor mixing. In this work, BeeBot was tested in the Sheffield Aerial Robotics Lab (SARL) which in addition to the above has a Vicon Motion Tracking System (MTS) [34]. The MTS provides ground-truth data about position and orientation within millimeter accuracy to supplement analysis. BeeBot and the SARL setup used in this work is shown in Fig. 1.

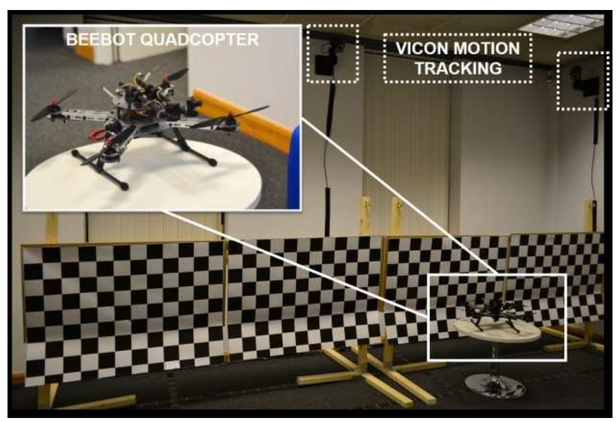

Fig. 1. BeeBot Laboratory Testing Scenario

B. *Design Specifications*

The design specifications are a result of the robot application and also the plausible testing environment described above. Maneuverability and small size allow are required for operation in most environments and in order to replicate the wide-range of flying insect behaviors. Additional size and communication requirements are a result of the laboratory testing and additional safety in the event of failure [35]. Payload requirements are a result of the application domain. Lastly, the requirement for low cost is motivated to provide a wider user-base.

Design Requirements

- sUAV category with 6 DoFs
- Less than 2kg total weight
- Less than 0.5 x 0.5 x 0.5 meters in size
- Inexpensive (off-the-shelf components)
- Moderate payload capacity of ~350grams (due to high sensing payload)
- Replicate the insect-like visual input: fast, steady, course, wide field-of-view
- Replicate the insect-like olfactory input: array of various chemical detectors

The sUAV design is then evaluated against the design requirements and its suitability for further development. Therefore, the overall design parameters and their distributions (i.e. weight, size, cost, average flight time, and power draw) are assessed. Additionally, the sensor payload responses are evaluated for their applicability in higher-level neural processes like OF and odor detection.

IV. BEEBOT DESIGN

To address the embodiment of a honeybee behavior, this research proposes a quadcopter sUAV named BeeBot (see Fig. 1). It enables the fundamental capabilities of 6-DoF honeybee flight like hovering and vertical take-off/landing while allowing for a reasonable payload (necessary to equip a quadcopter with honeybee senses). Additionally, a quadcopter platform was selected due to their configurability, flexibility, simple mechanics, large-open-source community, low cost, and ability to support a moderate payload.

The BeeBot quadcopter was designed around the necessary payload (final design was 1800gram total) and to ensure appropriate and reliable camera data (for the study of embodied computational models of visual processing and for visual navigation). The quadcopter design was then optimized using the design iteration proposed for sUAVs [36].

A. *BeeBot Sensor Payload Design*

The unique configuration of sensors used here in the design of BeeBot include dual wide-angle lens cameras and an array of chemosensors to mimic honeybee vision and olfaction. These are motivated by the requirements of steady, quick, reliable data streams and a wide visual field-of-view. BeeBot also has other typical UAV sensors which include a 3-axis gyroscope, 3-axis accelerometer, magnometer, and GPS.

1) Vision

It is necessary to use cameras equipped with wide-angle lenses since insects have almost panoramic vision and use each region in the eye for different tasks. However, they also have relatively coarse vision which is dictated by the spacing and acceptance angles of the ommatidia. Since each ommatidium essentially functions as a pixel in an image, bee vision works out to be roughly 75x75 pixels which even low-resolution cameras possess. The implication of this is that a wide selection of off-the-shelf cameras will provide the necessary acuity, and that the limiting factor on most cameras will be the field-of-view and weight. Because their vision is so coarse (and therefore, they don't require as much visual information), there is no need for high-definition cameras for insect-inspired embodiment, but moderate performance is desired for visual navigation applications.

To balance these requirements, the BeeBot was fitted with 2 mini CCD FPV (First-Person View) cameras with wide-angle lenses (see TABLE I). These are general, inexpensive, and commercially-available cameras that stream their video wirelessly. The cameras are fixed off rigid legs which are secured atop of an anti-vibration mount to reduce rolling shutter.

TABLE I
BEEBOT CAMERA SPECIFICATIONS

Quantity	Value
Manufacturer	Turnigy
Model	Micro FPV Camera 600TVL
Region Encoding	NTSC
Resolution	768x494
Frame-Rate	30FPS
Lens Viewing Angle	150º
Lens Diameter	2.1mm

The 2 cameras are mounted symmetrically off the front of the quadcopter in a similar orientation to that of honeybee eyes (see Fig. 2). In this configuration, each wide-angle lens has a field-of-view of 150º (again, similar to each bee eye). Unlike the bee, the binocular overlap of the BeeBot is closer to 60º (as opposed to ~30º). This is to minimize loss of information in the front of the quadcopter's field-of-view due to distortion from the lenses. In total, the chosen configuration results in BeeBot's field-of-view to be ~240º horizontally and ~150º vertically (very similar to the bee's ~280º by ~150º).

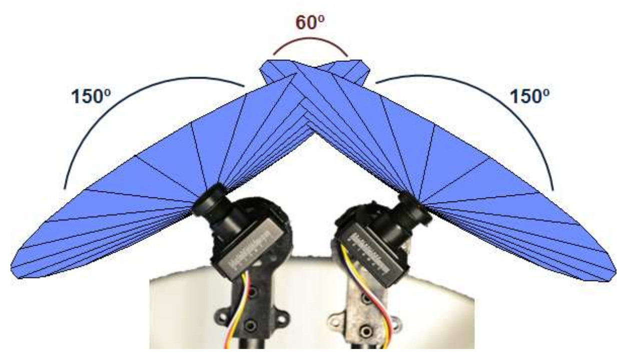

Fig. 2. BeeBot's Field-of-View

Data from each camera was transmitted over a 5.8 GHz 20mw FPV transmitter to an 8CH Diversity A/V receiver compatible with generic USB capture cards. These low-power transmitters are suitable over the short distances required. The resultant communication between BeeBot and the Ground Control Station (GCS) is shown below in Fig. 3 including the telemetry data and command signal connection which is sent over a 2.4GHz Xbee data link.

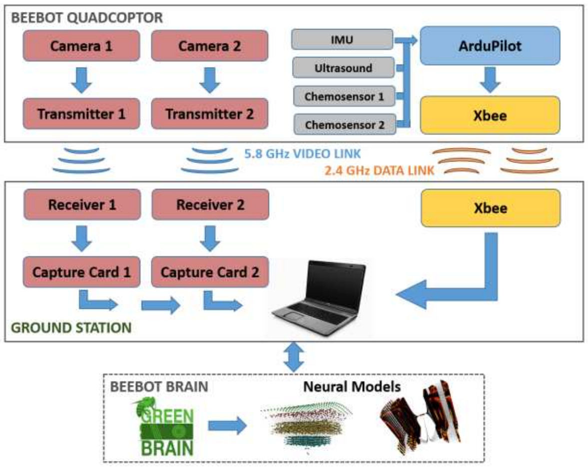

Fig. 3. BeeBot to Ground Control to Brain Interface

The output from the cameras could then be processed and utilized for various uses on the GCS. More traditionally with sUAVs, the data is then processed for computer vision applications (e.g. for SLAM, object detection, OF, etc.). In our example however, BeeBot is used as a basis to study neural models based on flying insects as also shown in Fig. 3. The GCS communicates with a GPU which parallelizes, and so speeds up, the computations needed to process the models. In either case, the visual output from the cameras can be used to calculate the OF and detect objects (i.e. like flowers or obstacles) which are implicated in insect visual flight behaviors and cognition.

2) *Olfaction*

BeeBot is also equipped with the commercially-available Figaro metal-oxide gas sensors depicted in Fig. 4 [37]. The types selected are the TGS 2600, TGS 2602, and TGS 2620 which are used to detect general air contaminants like volatile organic compounds, ammonia, methanol, etc. in office and home environments. Suitable environments for these olfactory sensors include office space, home, and lab.

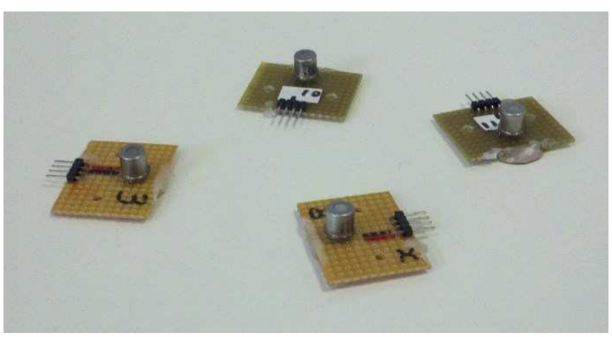

Fig. 4. BeeBot's Figaro TGS Chemosensors

Each chemosensor has a sensing element and integrated heater. The sensing element is comprised of a metal oxide semiconductor layer which changes conductivity depending on gas concentration in the air. Sensor conductivity can be related to a voltage reading using a simple electrical circuit. This voltage reading then directly reflects the gas concentration. Each sensor only requires 42mA at 5V of power. As a result, the chemosensors can be connected through the ArduPilot, and the data can be sent over the 2.4GHz connection.

While the BeeBot only has 3 types of chemosensors, it should be able to distinguish 2 different odors or pick out 1 odor in a mixture with this setup. Even though BeeBot doesn't have as many chemical sensor types as the bee, it is able to reproduce the sensor response and therefore, some of the behaviors that utilize olfactory information.

B. *BeeBot Platform Design*

The quadcopter design process proposed by Bouabdallah for sUAVs was used here and first chooses a propulsion group based on overall weight [32]. Quadcopters over 1kg are typically designed with a motor specification between 700-900Kv (and between 1300-2200Kv for less than 500g). For steady flight at this size, an 8-12" propeller would be appropriate where 4-6" would be for smaller, faster designs. Therefore, a "higher" motor speed for its size (950Kv) with medium sized propellers (10x4.7) is chosen as this ensures a balance between design specifications and maneuverability. The final robot utilized APC 10x4.7 propellers, HobbyWing A2217-9 motors, 18Amp ESCs, and a 25C 11.1V 5400mAh Thunder Power battery. The propulsion group shows the appropriate thrust (~1kg for each motor) and high efficiency (>80%) at the desired 7500RPMs and average 19A draw.

For this propulsion group and size, the BeeBot quadcopter utilizes a 24" Aeroquad frame [38], an ArduPilot autopilot [39], and the custom sensors discussed above. This size makes it suitable for both large laboratory environments and outdoor flights. ArduPilot was chosen as it is open-source and has a large community for support. This is ideal for this case, because the quadcopter will need to support a unique configuration of sensors. An autopilot that is open-source allows it to be modified as needed. The reasonably small frame makes it more conducive to flying indoors but also supports the necessary sensor payload required.

In addition to the components needed to embody honeybee senses, the quadcopter/autopilot is equipped with traditional sensors like an inertial measurement unit (which has a 3-axis accelerometer, 3-axis gyroscope, and magnometer), air pressure sensor, and ultrasonic sensor. While most quadcopters also have GPS, the BeeBot does not as it primarily flies indoors as stated in the design requirements (Section III).

As stated, the quadcopter is controlled remotely via wireless networking. The ground station processes visual data received from the robot's cameras, manages olfactory information from the on-board gas sensors, and runs heavy computing processes. While ultimately it is desirable to do all computing on-board, physical space and weight restrictions limit how much can be done. Furthermore, this setup means that heavy visual computing and/or neurological models can be run in real-time to control the quadcopter. This would not be realizable with an on-board setup with off-the-shelf components at this time.

V. RESULTS

The testing and results evaluate the final design which includes both the platform and sensor payload performance.

A. *BeeBot Design Results*

The final BeeBot design is detailed below in TABLE II. The total cost was $1,500 and had a weight of 1840 grams (both within the requirements). The propulsion group had an average power draw of 200W which results in a ~8 minute flight time. The total weight, power (average usage), and cost breakdown is shown below in Fig. 5, Fig. 6, and **Error! Reference source not found.**, respectively.

TABLE II
BEEBOT DESIGN RESULTS

Quantity	Value
Total Weight:	1840 grams
Total Size:	75 x 75 x 40cm
Total Cost:	$1,500
Average Power Draw:	225 Watts
Average Flight Time	8 Minutes

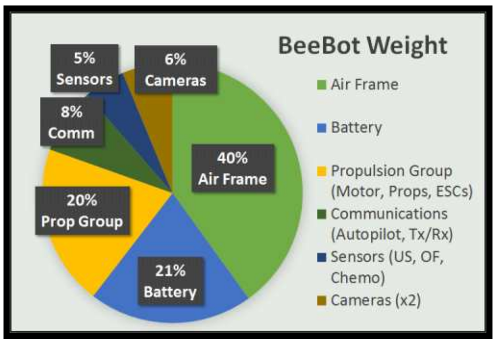

Fig. 5. BeeBot Weight Breakdown

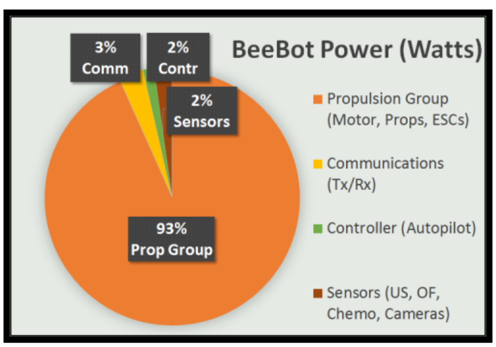

Fig. 6. BeeBot Power Breakdown

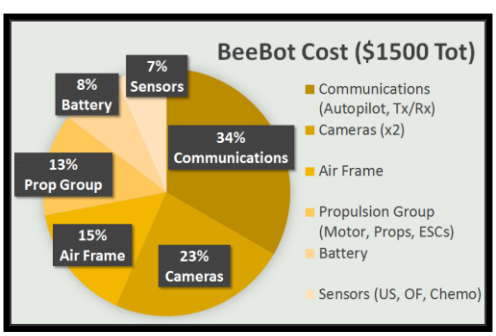

Fig. 7. BeeBot Cost Breakdown

B. *BeeBot Sensor Payload Results*

BeeBot sensor payload results are an outcome of testing the impact of the specific hardware component selection for feasible use in insect embodiment and navigation problems. For flying insects like honeybees, neural processes like OF and odor detection are crucial to navigation.

A benchmark problem used for flying insects is the hallway navigation test. Therefore, a scaled laboratory environment of this experiment is used to test BeeBot in. The lab was configured with two walls along the length (fitted with a checkerboard pattern) and a motion tracking system providing ground truth data as shown previously in Fig. 1. In each test, BeeBot starts at one end of the hallway and then travels to the other end at a fixed velocity for a number of trials.

1) *Vision*

As stated previously, the visual outputs are primarily used for replicating insect flight behavior based on OF. To enable this, the raw camera data needs to be processed to model insect vision accurately and to calculate the OF.

The methodology presented by Sabo [40] was followed for modelling camera intrinsic and lens distortion values as well as for modelling honeybee vision and subsequent pixel selection. An example of the output data from BeeBot in the hallway is shown below in Fig. 8. Both the original view and final insect view can be seen.

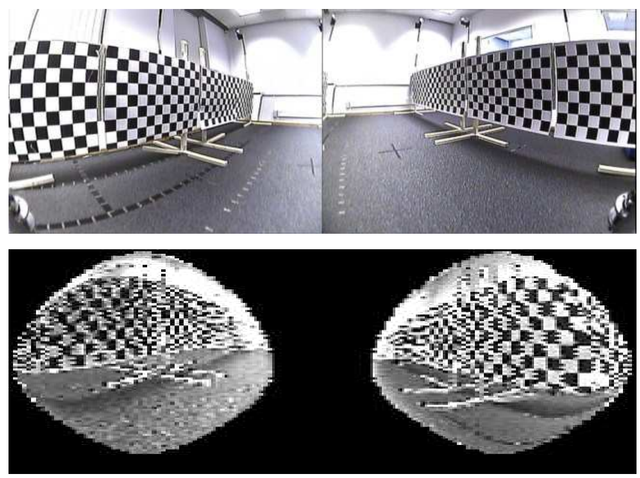

**Fig. 8. Image from BeeBot Camera Output – Original View (Top)
Image from BeeBot Camera Output – Insect View (Bottom)**

As BeeBot moves down the hallway, OF is generated and can be calculated off-board at the GCS. Typically, computer vision algorithms are used, but we utilize a neural-based approach to OF calculations here. Measurements are computed using a biological model of motion detection. The Angular Velocity Detector Unit (AVDU) model is founded on the Reichardt Detector which is based on EMDs in the insect eyes [33]. The AVDU model calculates angular velocity which is summed over each of the cameras (or "eye") and shown in Fig. 9.

The results show the raw and average response from 12 trials when presented with a 98mm square grating. For each trial, the robot followed the same path which was approximately centered in the hallway (5cm closer to left wall), and the velocity was kept constant at 0.3 meters/second. As expected, the left values are consistently larger than the right even though it is by a small amount, and variations are relatively low. The deviations towards the end of the trials are also as expected, because the robot gets closer to the end of the lab and the view of the hallway is behind the robot and limited.

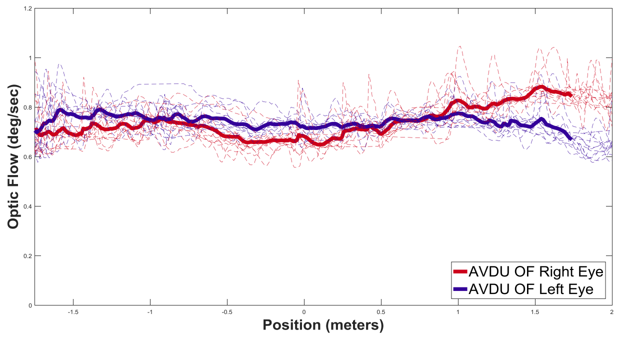

Fig. 9. BeeBot AVDU Model OF Output
Left and Right camera/eye over the trials is depicted for each trial (light, dotted line) and the overall average (dark solid line).

2) Olfaction

The olfactory system in insects is primarily used to identify the presence of odors and distinguish odors in a mixture. The odor cues can then be used for a variety of tasks in insects but of interest here is how they relate to navigation.

Again, experiments on olfaction were completed in the indoor laboratory which provides a semi-controlled environment. The practicality of using the 3-chemosensor combination was tested by arranging an odor source at the end of the hallway in front of a small, low-powered fan. In each trial as the robot moved towards the odor source, it took readings at 1 second time-steps. Large fans were turned on to help clear room of residual odors between trials. A total of 3 trials were performed each for 2 odors (orange essential oil and ethanol). At the start of each trial, a Baseline Value (BV) was taken and averaged over 10 seconds. The response of the chemosensor is then calculated by dividing the Sensor Value (SV) by the BV for that trial.

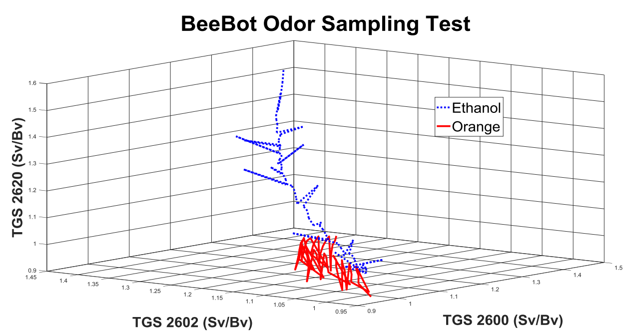

Fig. 10. BeeBot Odor Sampling Chemosensor Output
The averaged response from the 3-chemosensor readings are depicted for 2 different odors (ethanol in blue and orange in orange).

The chemosensor value for each type of sensor is the average of the responses over the trials and shown in Fig. 10. For all the sensors, the response to different odors is fairly steady after they reach their maximum value (5-20 seconds) if the robot is still. However as the robot moves, sensors do not have this time to reach a steady state value, and the control system may need to distinguish odors at a faster rate. It can be seen that although the response for the two different odors are initially the same, they converge to different points over time. Not only do they diverge to separate points, they do so within the first few time steps. This is especially apparent as the robot approaches the odor and the values differ considerably.

This analysis shows that our sensor payload has good potential for odor discrimination for robotics applications. This discrimination and learning by the olfactory system could be done with a neural reinforcement learning approach with rewarded odors as in real-life for instance. Even though the responses diverge in state space, it is still slow to converge compared to the frequency needed for low-level flight control commands. Therefore, the use of this signal would be more suitable for higher-level navigation decisions (e.g. switching flight modes or targets).

VI. Discussion

Embodiment of honeybee-like cognition is achieved here using a quadcopter sUAV as a platform, dual wide-angle lens cameras for vision, and chemosensors for olfaction. It was shown that insect vision can be replicated with relative similarity in field-of-view and also resolution by some post-processing of the visual input. Bee's ability to distinguish odors is reproduced using multiple types of chemosensors which lends itself to neural mechanisms which can discriminate and learn odors.

As discussed earlier, the temporal resolution of the bee's eye is up to 300 Hz (much quicker than human vision). However, the camera system deployed on the BeeBot is only capable of 30 fps. While this is sufficient for robot visual navigation, it is much slower than the bee requires. To accurately represent the visual input in higher-level cognitive models, there are a few compromises that could be made: (1) do pixel selection on-board to reduce the size of the data, (2) slow the models speed down by 1/10th so that the models can still get data and can control the quadcopter in real-time, or (3) spend significantly more money to improve hardware.

The slow settling time of the chemosensor's response will make quick navigation by searching for odors challenging. However, these experiments can similarly be slowed down to still reasonably model bee response and behavior. Also, the change in voltage can be seen relatively quickly. Therefore, rapid actions can still be selected based on odor response change, but informed decisions would still be difficult.

The BeeBot design meets all of the design requirements but falls a little short in the response time. This was mainly due to the choice of using inexpensive, off-the-shelf components. This could be improved by reducing the overall size of the platform and using smaller propellers. However, the sensing payload would still need to be a significant percentage of overall weight. Another desirable trait would be to move all computing on-board BeeBot to increase autonomy. However, the next steps require a reduction in overall size and weight which can only be achieved with more money. This will improve development by increasing autonomy and computing capacity.

Despite some shortcomings, BeeBot is a considerable improvement over typical platforms used for embodiment. Most platforms used are ground robots which can usually only move in 3 DoFs despite flying insects having 6 DoFs. It also has less constraints in each DoF than normal ground robots. Finally, the range of sensing capabilities make this usable for high-level cognitive tasks which require multi-sensory inputs.

VII. Conclusion

Due to progress in the miniaturization of electronics, UAVs are becoming much smaller (<20lb) and more affordable. Advances in sensors, processing, and batteries have made these technologies low-weight, low-power, and low-cost and allowed these sUAVs to broaden their user group and applications. Despite their growth, they still lack the ability to demonstrate robust navigation and cognition like flying insects, and so there is extensive interest to enable sUAVs with insect-like abilities.

In this research, a quadcopter was designed and modelled and then tested and analyzed based on its suitability to embody insect flight behavior and cognition. BeeBot is a good proof-of-concept prototype demonstrating support of necessary payload to replicate the sensing capabilities which are vital to bees' flight navigation including chemical detection and wide visual field-of-view. Furthermore, this was done with inexpensive (~$1500 total), off-the-shelf components which are open-source and thus, good for research development.

The successes seen by neural models in reproducing robustness to real-life uncertainties need platforms for which the algorithms can be embodied and fully tested. Ultimately, this robot could be used for better understanding of honeybee flight behavior and cognition and the development of sophisticated visual flight control based on mimicking the natural world.

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