A bio-inspired apposition compound eye machine vision sensor system

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Abstract

The Wyoming Information, Signal Processing, and Robotics Laboratory is developing a wide variety of bio-inspired vision sensors. We are interested in exploring the vision system of various insects and adapting some of their features toward the development of specialized vision sensors. We do not attempt to supplant traditional digital imaging techniques but rather develop sensor systems tailor made for the application at hand. We envision that many applications may require a hybrid approach using conventional digital imaging techniques enhanced with bio-inspired analogue sensors. In this specific project, we investigated the apposition compound eye and its characteristics commonly found in diurnal insects and certain species of arthropods. We developed and characterized an array of apposition compound eye-type sensors and tested them on an autonomous robotic vehicle. The robot exhibits the ability to follow a pre-defined target and avoid specified obstacles using a simple control algorithm.

1. Introduction

The Wyoming Information, Signal Processing, and Robotics (WISPR) Laboratory is interested in exploring the vision system of various insects and adapting some of their features toward the development of specialized vision sensors. We do not attempt to supplant traditional digital imaging techniques but rather develop sensor systems tailor made for a wide variety of commercial, medical and military applications. We envision that many applications may require a hybrid approach using conventional digital imaging techniques enhanced with bio-inspired sensors.

This approach to sensor development has some precedence; Sanders and Halford noted 'Alternative methods modeled after the multi-aperture optical system of arthropods offer new ways to segment the object space of a sensor, increase the field of view, and perform low-level visual functions relatively easily, inexpensively, and quickly. [...] There are many reasons for investigating biological apposition compound eyes as paradigms for manmade systems. [...] Insects and crustaceans perform many perceptually oriented

tasks with their compound eyes, such as obstacle avoidance, landmark recognition, searching for mates and food, and avoidance of predators. Many of these tasks are essentially the same as the tasks required by artificial sensor platforms, and arthropods accomplish these with simple neural processing systems compared to those of vertebrates.' [1].

In this project, we investigated the characteristics of the apposition compound eye commonly found in diurnal insects and certain species of arthropods. We developed and characterized an array of sensors configured similarly to an apposition compound eye and tested them on an autonomous robotic vehicle. The robot exhibits the ability to follow a specified target and avoid pre-defined obstacles using a simple control algorithm much like an insect searching for a mate or food and avoiding predators [2, 3].

We begin with a brief review of apposition compound eyes and related historical work in biologically inspired autonomous vehicles, followed by a discussion of the apposition compound eye sensor, array layout and our small autonomous vehicle equipped with an algorithm for target



Figure 1. Insect vision configurations: (*a*) apposition, (*b*) superposition, and (*c*) neural superposition. Adapted from [4]. Published with permission of ISA. Copyright 2008. All rights reserved.

tracking and obstacle avoidance. Sensor characterization along with tracking and avoidance results is then provided.

2. Background and related work

This research effort investigated the potential for building a system that exhibited complex behavior using a sensor and processing based on apposition compound eye vision. Our primary research goal was to perform experiments with an autonomous vehicle with such a bio-inspired vision system and a very simple controller. In this section, we briefly review related work in these areas.

2.1. Types of insect vision

Land [4] describes the basic configurations of insect vision, including apposition, superposition and neural superposition compound eyes and the acuity characteristics of each. Each configuration has its own inherent advantages and disadvantages. As can be seen in figure 1(a), in an apposition compound-type eye the rhabdomere (light sensitive cell) bundle, called the rhabdom, has its own lens. The individual light gathering contributions from each rhabdomere is pooled. The spatial acuity of the apposition compound eye is primarily determined by the interommatidial angle ($\Delta \phi$) described by

$$\Delta \phi = D/R$$

where D is the diameter of the facet lens and R is the local radius of curvature of the eye [4]. As can be seen in

figure 1(*a*), $\Delta \phi$ describes the angular displacement between adjacent ommatidia. The optical superposition eye pools light from adjacent ommatidia as shown in figure 1(*b*). This effectively enhances the light gathering capability of this insect vision configuration but reduces the effective acuity due to the blurring effect of spatial superposition. In the neural superposition eye, illustrated in figure 1(*c*), one rhabdomere in seven adjacent ommatidia shares an overlapped field of view with the other. These overlapped fields of view provide a motion resolution greater than that implied by the photoreceptor spacing of the retinal array, a phenomenon known as hyperacuity [5].

Our research group has researched fly-inspired vision sensors for a number of years. It is important to note that most of these sensors are of the neural superposition compound type. A thorough review of this type of sensor and its characteristics is provided in [6]. In contrast, the work described in this paper is of the apposition compound-type eye commonly found in diurnal (daylight) insects and certain species of arthropods.

2.2. Related vision behavior

Beyond modeling an apposition compound-type eye, we also wanted to investigate and model some of the aspects of the apposition compound eye exhibited by certain diurnal species including adaptation to various lighting conditions, processing of photoreceptor inputs and pattern matching for navigation. These aspects of apposition compound eye vision seemed to lend themselves readily to simple electronic implementation of a similar sensor, which when paired with a simple control algorithm could lead to interesting autonomous behavior.

Mazokhin-Porshnyakov made the following observation about apposition compound eye-type vision systems: 'Considering the extremely small dimensions of the corneal lenses we can expect eyes of such type to be of little use for vision in weak light. In fact, apposition eyes are present almost exclusively in diurnal insects.' [7]. To compensate for this limitation, insects use a variety of adaptations. Recent work by Greiner *et al* [8-10] has shown that certain species of nocturnal bees may use neural summation of light in time and space to visually orient to landmarks at night. Greiner also noted that pigment migration during light and dark adaptation 'constitute the most important pupillary mechanism found in compound eyes' [11–13]. There is also evidence that photoreceptors of diurnal animals adapt their properties according to current illuminance allowing them to function in light that may change over eight orders of magnitude [14]. Laughlin also reported that various actions adjust the large monopolar cells 'sensitivity to the background intensity so that their responses code contrast fluctuations rather than absolute intensity' [15]. Harris et al supported this theory indicating 'adaptation in retinas shifts the operating range of photoreceptors and neurons to match the prevailing stimulus distribution' [16]. In this research effort, the robot performs a light adaptation routine to adjust to ambient light conditions. The robot senses the ambient light conditions and automatically adjusts the analogue electronics operational parameters. This provides for a wide dynamic range of sensing for various light conditions.

As previously mentioned, Greiner *et al* [8] hypothesized that nocturnal bees may use neural summation of the apposition compound eye photoreceptor input in time and space to orient to landmarks at night. This appears to be counterintuitive since summing the photoreceptor inputs would have a blurring effect. However, related work by Goldhoorn *et al* indicates that combining this information into an average landmark vector [ALV] may be a powerful method of navigation and homing. An ant species from the Saharan desert, the Cataglyphis, uses this technique for visual homing [17–19]. In this research effort, we employed a similar technique to ALV. We calculate a center of mass (COM), a weighted average of sensor inputs, as a method of combining the sensor inputs to assist in robot navigation.

In addition to the COM processing, we employ a pattern match technique to determine robot behavior. The pattern of obstacles and targets is considered against pre-defined patterns to determine the robot's response. This is similar to a number of techniques well documented in the literature used by a wide variety of species including bees, ants and fish [9, 20–23].

2.3. Bio-inspired autonomous vehicles

In 1948, Norbert Weiner published *Cybernetics*. Weiner focused on parallels between mechanical systems and living systems. *Cybernetics* was soon followed by the experiments of Dr Grey Walter, an English physician. Walter constructed a number of small autonomous vehicles in the 1950s that he referred to as an 'imitation of life' [24–26]. His 'turtles'

were wheeled vehicles with a control system made up of several vacuum tube circuits and sensors. They were able to seek light, avoid touching walls and connect themselves to a power source to recharge their batteries. By 1953, Walter had constructed a system that was able to use oscillatory circuits as the memory for rudimentary learning. An important feature of his cybernetic work was the use of analogue computation elements.

From the late 1950s through the 1970s, the growing availability of digital computers caused a shift away from cybernetics towards artificial intelligence (AI). Classical AI concerns itself with the use of world models and symbolic logic to make inferences and plans from input data. This approach showed high initial promise, especially in the areas of game playing and symbolic math. The traditional AI approach did not have a great deal of success dealing with the complexity of real world sensor input encountered in the development of autonomous systems, primarily due to problems with the creation of accurate world models [27, 28].

The 1980s saw the return of reaction-driven rather than model-driven approaches to autonomous mobile systems. Rodney Brooks and his research group at the MIT mobile robot lab introduced a control system model that uses simple computations to map sensor inputs to actuator outputs. A number of these mappings are then combined in what he calls a 'subsumption' architecture to enable the construction of a robust system capable of operating in an environment with little or no structure. This approach has led to the construction of robots able to walk or roll across unstructured environments with little or no supervision [28].

In 1984, a well-known neuroscience researcher named Valentino Braitenberg published *Vehicles*. Braitenberg presented a series of hypothetical 'vehicles' of slowly increasing technical complexity, but of quickly increasing complexity of behavior. The vehicles range from ones similar to the ones built by Walter to more complex ones incorporating learning and motion detection. The thought experiments presented in *Vehicles* seem to have had a strong influence on later work by others. The book is deceptively simple, and is focused on the idea that systems of relatively simple design can exhibit surprisingly complex behavior [29].

In 1992, Franceschini et al performed ground breaking work inspired by Braintenberg's 'vehicles'. In this research effort, a small robotic vehicle was equipped with a complement of 100 elementary motion detectors (EMDs) inspired by the neural superposition eye of the fly. The vehicle was able to track an active stationary lamp as a target. The robot was able to navigate about obstacles and track the target at speeds up to 50 cm s⁻¹ [30]. The work described in this paper is a natural extension of Franceschini's research. However, unlike Franceschini, an apposition style compound eye vision system found in a wide variety of species including diurnal insects, ants, bees and certain species of arthropods is employed. Furthermore, a center-of-mass tracking algorithm inspired by these species is used to navigate about obstacles and track a moving target using passive sensing techniques at speeds up to 100 cm s^{-1} . The goals between the two projects are similar: track a target while navigating obstacles using simple systems inspired by species within the insect world.

2.4. Contemporary machine vision

The main thrust of the research by Koch, Reid and Higgins is in building systems based on EMDs which can be attributed to Reichert. EMDs basically work by correlation of information from two adjacent photo cells. The present and delayed input to each cell is combined to determine if one detector is seeing what the adjacent detector saw a moment ago. The EMD produces a bipolar output signal with the sign indicating the direction of motion. An array of EMDs together can detect visual flow [31–36].

Fearing is building a micro aerial vehicle (MAV) equipped with motion detectors (based on EMDs), microelectromechanical sensors used to measure body rotations and artificial ocelli which are used by insects in horizon-based attitude control. The control system for the insect is based on a hierarchical decomposition of the control functions [37, 38].

Neumann has been using insect-inspired vision algorithms to develop flight control models. The work consists mainly of computer simulations of EMD-equipped unmanned aerial vehicles (UAVs) flying through simulated environments. The simulations use a very structured textured environment and a simple flight model. Translation and rotation-induced optical flow is calculated and used to calculate velocity and altitude, as well as computing attitude. EMDs form the basis of the vision algorithms [39–41].

Franceschini and Netter have work similar to that of Neumann, but using a physical UAV instead of a simulated one. They have constructed a system which includes a UAV tethered to a pantographic arm which restricts the pitch and altitude of the UAV to limited ranges, while completely limiting the roll and yaw. As the UAV flies, the attached arm is pulled around and up and down; the position of the arm as well as rotor commands to the UAV is passed by a slip ring. A ramp with a pattern painted on it lies below the flight path, and the UAV is equipped with an array of EMDs which are used to control its flight. Over 50 successful automatic terrain following flights have been accomplished with this system. The EMD integration is done digitally, and the visual pattern used on the flight surface is similar to that used in Neumann's work [42].

The United States Naval Research Lab (NRL) and Centeye have also been doing work similar to that of Franceschini, Netter and Neumann, but their experimentation has been conducted in less-structured environments. Using a variety of flying platforms from small glider models to UAVs, they have demonstrated the usefulness of insect-based vision in UAVs operating in an unstructured environment [43, 44].

3. Methods

In order to perform the series of experiments required to explore the viability of an artificial apposition compound eye system, quite a bit of system development had to be performed. In this section, we detail the development of the sensor element, array layout, the processing and control algorithm, and the adaptation of a low-cost, ground-based vehicle. The bulk of the equipment was developed with offthe-shelf components.

3.1. Sensor development

Nearly all animals that have vision systems exhibit both seeking and avoiding behaviors. Virtually all animals seek food and mates, and they must avoid predators and obstacles in nature. The goal of this project was to develop an apposition compound eye vision system that would allow an autonomous system to exhibit these kinds of behavior in a semi-structured environment. Based on this goal, the following requirements were established.

- Sensors shall be passive and operate at visible wavelengths.
- Sensors shall be able to operate under ordinary indoor lighting conditions.
- Sensors shall be able to provide output that allows for discrimination of a target versus an obstacle on the basis of shade.
- Sensors shall be able to detect objects at a range which is large compared to the size of the vehicle.
- Sensors shall have angular sensitivity in the range of $2-10^{\circ}$.
- The sensor array should be able to determine bearing to an object (target or obstacle).
- The array should be of a reasonable physical size (i.e. on the order of the robot's width).
- The array should maximize the total field of vision relative to the mounting footprint.

Sensor array coverage is a trade-off between the angular sensitivity of a single sensor and the number of sensors employed in the array. The individual sensor sensitivity selected allows for a target object (about 250 mm wide) to take up the entire field of view at the sensor's nominal range. In other words, the field of vision is about 300 mm wide at a range of 3 m, and the target is also about 300 mm wide. To provide sufficient angular coverage in front of the vehicle required a sensor array consisting of seven individual sensors as shown in figure 2.

An individual sensor consists of a photodiode, a lens for focusing and gathering light, the mounting hardware and the support electronics as shown in figure 3. After evaluating alternatives, the TAOS TSL251R photodiode with an integrated transimpedance (current-to-voltage) amplifier was chosen [46]. Each photodiode was equipped with an integrated lens providing a field of vision on the order of 60°. To achieve better angular selectivity and range characteristics, an additional spherical plano-convex lens (f = 12 mm) was mounted on the front of each detector assembly. The final sensor module design had a field of vision of approximately 5° and a useable range on the order of 3 m.

The sensor output was passed to a Twin-T notch filter [46] to eliminate the 120 Hz noise from fluorescent lights. Additionally, a low-pass filter was also employed to remove high frequency noise that was present in the raw sensor output.

The output from the filtering stage was fed to a digitally controlled level shifting stage. The purpose of this stage is to



Figure 2. Top of the robot. The interommatidial angle of 6° has been superimposed on the diagram.



Figure 3. A single apposition compound eye sensor. Published with permission of ISA. Copyright 2008. All rights reserved.

maintain the output sensor level given various ambient lighting conditions. This is accomplished by sensing the ambient light conditions and generating a corresponding offset voltage from a digital-to-analogue converter which is fed back to the filtering stage for use as a bias. To provide the maximum dynamic range for the detection of black targets and white targets, two different bias levels are calculated. During operation of the sensor, the offset can be adjusted for optimal detection of either target type.

After considering various sensor information processing algorithms, a 'tri-state' (light shaded, dark shaded, ambient) object detection algorithm was chosen. The 'tri-state' sensor provides less information than a continuous value sensor output, but it is extremely robust. When configured properly, it was able to detect that either a target (black object designated T), an obstacle (white object designated O) or nothing (ambient designated A) was present within a specific sensor field of view. Further, it is capable of categorizing these objects while in motion. The final output from an array of these apposition compound eye sensors is a trinary-valued one-dimensional

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vector, for example OOAATTT. The vector indicates what is currently in the field of view of the sensor array.

3.2. Controller

To achieve the overall goal of the system, it is necessary to have an intermediary between the sensors and actuators the controller. Essentially the controller is an algorithm implemented on a microcontroller. The general approach to algorithm development was to partition the algorithm into two major portions: (1) track a target and (2) while avoiding obstacles. The first step in designing the algorithm was to try to get each behavior working on its own.

Figure 4 is a flowchart illustrating the algorithm used for tracking and avoidance. The basic approach is simply to provide the servo with an input command that is proportional to the bearing to the target. If no target has been seen, the algorithm waits to send any commands until a target appears. Once a target does appear, the algorithm performs a center-ofmass calculation of thresholded sensor outputs. The centerof-mass calculation results in target bearing. For tracking,



Figure 4. Control algorithm. Specific reactions to obstacle and target pattern stimulus are programmed as a series of decision statements. Once a specific pattern has been found, the vehicle executes a pre-determined maneuver specific to the stimulus pattern.

platform heading is driven to minimize the target bearing to zero. If a turn is required, the controller begins issuing servo commands and the drive motor is turned on for forward motion. If the target disappears, the algorithm continues to command the vehicle to turn in the same direction it was turning when the target disappeared. This persistence is meant to allow the system to deal with very tight turns by the target vehicle.

Obstacle avoidance is similar to tracking except that instead of trying to minimize object bearing, the obstacle avoidance algorithm works to maximize it. Because we assigned high cost to hitting obstacles, instead of turning away from the obstacle proportionally the turn is made as hard as possible in the opposite direction. Once the obstacle has been cleared, the vehicle steering is straightened. If an obstacle is directly centered in front of the sensor array, the robot has an arbitrary preference to turn right.

Combining obstacle avoidance and target tracking presents a number of problems. We have already stated that we assign high cost to a collision with an obstacle. Because of this, if the commands do not conflict the command from the obstacle avoidance algorithm is preferred. However, there are cases where the commands are in conflict. The general approach to the problem was to investigate the possible cases and to create a logical structure that allows for the combination of the two algorithms into one appropriate behavior from the two possible actions. The most challenging case involves obstacles on both edges of the field of view. If the obstacles are far enough apart, the controller attempts to pass between them. If the obstacles use up too much of the field of view, the obstacle avoidance behavior takes precedence and the vehicle maneuvers to open one side of the field of view.

It is interesting to note that for either the case of target tracking or obstacle avoidance, the critical computation done is finding the center of mass of an object in a binary image. In the experimental implementation, this is accomplished using a microprocessor, but it could just as easily have been computed prior to being digitized using analogue components such as comparators, op-amps and multipliers. Well-known circuits for the computation of weighted averages and sums can be readily found in the literature [47]. Processing of data in this fashion should allow very high throughput with little hardware, and is more consistent with the biological systems from which our approach is derived. To combine tracking and obstacle avoidance under this paradigm is non-trivial, but can be accomplished using combinational logic circuits as the current algorithm purposely does not have any memory or state.

3.3. Ground-based vehicle

An off-the-shelf Kyosho scale model car was chosen as the project vehicle due to desired features of electric drive, proportional control of steering and speed, and low cost. The vehicle is 460 mm long, 198 mm wide and 145 mm tall and weighs 1680 g [45]. The weight is approximately doubled with the sensor and control hardware mounted. The vehicle has a top speed of approximately 3 m s⁻¹ and a turn radius of approximately 1.5 m.

Power for the drive motor and steering servo is provided by a 7.2 V battery pack. The electronic speed control and the steering servo are controlled by pulse width modulated (PWM) signals. The nominal period of the control signal is 20 μ s with command duration centered around 1 μ s. Deviations in speed and direction are made by varying the on time of the PWM signal. Optical isolation is used to prevent noise from the motor operation and speed control from affecting the control and sensor circuits. All of the control and sensing electronics are powered by an independent 5 V power supply. The control and sensing electronics as well as the optics are mounted on a sheet of acrylic that is bolted at three points to the vehicle as shown in figures 5 and 6. Figure 2 depicts the interommatidial angle of the apposition compound eye sensor, which is approximately 6°.

4. Testing and results

The system was tested in three main phases: (1) measuring the characteristics of a single sensor operating independently,



Figure 5. Side of the robot. The apposition compound eye vision array is mounted on the front of the robot beneath the plexiglass support structure. The array analogue processing electronics and digital processor are mounted on the support structure. The robot operates autonomously to navigate about an unknown environment to avoid obstacles and follow and intercept a target robot.



Figure 6. Front of the robot. The apposition compound eye vision array consists of seven apposition compound eye sensors yielding an interommatidial angle of 6°. Published with permission of ISA. Copyright 2008. All rights reserved. (This figure is in colour only in the electronic version)

Table 1. Layout comparison data.			
Layout	Base width (mm)	End width (mm)	Ratio
Linear 19 mm	150	400	2.66
Linear 50 mm	400	610	1.53
Linear 100 mm	812	965	1.19
Stereo	400	1575	3.94
Fan	150	2210	14.73

(2) measuring the characteristics of an entire array of sensors and (3) testing the entire system in a variety of operational environments. We discuss the results of each phase in turn.

4.1. Phase I. Sensor testing

The goal of phase I testing was to provide a firm basis for choosing a layout strategy for the array. The field of view for a single sensor was characterized for both a dark and white object. The maximum response from each object was first determined and then the object was systematically moved about in a grid pattern to determine the -3dB points demarcating the sensor field-of-view lobe. The sensors were found to have a field-of-view lobe of approximately 6° with a -3 db range of 2 m for a black target and 2.5 m for a white target. The sensor continues to detect targets for another 500– 800 mm greater range beyond the -3 dB point. Array design was accomplished using these parameters

4.2. Phase II. Sensor array testing

Various array patterns were considered including a linear pattern, a stereo fan pattern and a single fan pattern as shown in table 1. The linear pattern wasted most of the available sensor coverage by overlapping the sensors too much. The primary advantage of the stereo fan pattern is its potential to determine object range using stereo techniques. However, it was determined that if the left and right sensor clusters were placed far enough apart from one another to provide reasonably sized intersection zones, the total width would be much greater than that of the test vehicle platform. The single fan sensor arrangement was chosen primarily due to its superior total field of vision when compared to the other array configurations.

The chosen array behaved as would be expected from its geometry and the previously discussed properties of the individual sensor modules. To test the array, a grid was laid out on the laboratory floor. A grid point was placed every 150 mm and the grid was set up to be about $2 \times 2 \text{ m}^2$. The center of the sensor array was placed at a grid point and then targets were placed at other grid points. The individual sensors were able to detect objects that sufficiently occluded their lobes. These characterization tests formed the basis of the processing and control algorithm designs.

4.3. Phase III. System level testing

In phase III, the test vehicle equipped with an apposition compound eye sensor array was tested under a variety of conditions of increasing difficulty. The test setup consisted of a 3 × 4 m² corral of light colored tables turned on their sides to create the ambient background. The corral was equipped with a 1000 W halogen lamp at the open end. Additionally, lighting was provided by both sunlight and overhead florescent lighting. A video camera (720 × 480 pixels, 30 frames s⁻¹) was mounted 3.5 m above the corral.

The following tests were accomplished in this phase.

- Obstacle avoidance when only obstacles are present.
- Target tracking when only the target is present.
- Tracking and avoidance in an environment with static obstacles and a static target.
- Tracking and avoidance in an environment with static obstacles and a dynamic target.

Space does not permit a discussion of all results. We concentrate on the most difficult task from phase III: track and approach a target while simultaneously avoiding obstacles. Again, this mimics an animal with an apposition compound eye vision system searching for a mate or food while avoiding predators. Various obstacle arrangements were tried. Most of them follow an approach of building two parallel 'fences' of obstacles, placing the target in between the 'fences' and then placing some random obstacles in the tunnel. This arrangement is chosen for two reasons: first, it shows that the vehicle is programmed to have a preference for target seeking if the target can be located in the middle three sensors and, second, it shows that the vehicle will seek out the target while obstacles are present and hence meets the stated goal of the project. Figure 7 shows one example of the results of the test.

Figure 8 provides quantitative results from a representative test. The speed plot indicates that the two vehicles were moving at approximately the same speed. The range to target plot indicates the chase vehicle caught up with the target vehicle twice. The bearing plot indicates the interplay of the tracking behavior and the obstacle avoidance behavior. In a strict tracking scenario, the bearing would be expected to remain closer to zero, but because of the influence of obstacles the vehicle does not always try to achieve zero bearing.

5. Discussion

A number of issues were identified during the testing process as follows.

- (i) The behavior appears to be indecisive, turning the wheels all the time, never just heading straight for the target.
- (ii) The obstacles make the robot swing widely to the left or right, while the target only creates proportional corrections.
- (iii) The robot moves very slowly. This is less apparent in the frame sequences, but is clearly apparent in the actual test video records.

These issues are all legitimate; they are caused by design decisions made in the development and their solutions are nontrivial. Issue (i) is a direct consequence of the design of the



Figure 7. Dynamic track and avoid. In this test scenario, the target was dynamic and followed the 'plus' track. The chase track is shown in the 'dot' track. The tracks plot the center of mass of the vehicles. The chase vehicle track clearly shows the influence of the obstacle avoidance algorithm.



Figure 8. Speed, range to target, bearing to target from the dynamic track and avoid sequence. In the range to target plot, 400 mm is marked because this indicates the approximate distance from the vehicle center for interception. Intercept or near misses occur at approximately 0.66 s, 2.33 s and 5 s.

control algorithm. The vehicle looks as if it is 'trying to decide what to do', because it is. It is a response-based controller, and

there is no sophisticated decision process involved. It takes the current vector of array data, performs an algorithm to make a

decision and sets speed and direction accordingly. It does this again and again and again. Rather than making any plan, or having any knowledge of the past, the vehicle does the best it can at each time instant, hopefully leading it to a solution to its current problem.

A more complex design would start to solve this problem by incorporating a memory of the past state of the system. Knowing the previous position of the target, and the previous state of the obstacles, would allow the vehicle to make smoother changes in its direction. Incorporating a simple version of this would entail little more than averaging the previous target command and obstacle command into the current one. This would smooth the movements, but might not lead to any behavioral improvement.

Issue (ii) is partly caused by issue (i) and partly caused by the selected number of sensors. The algorithm could make proportional corrections for obstacles the way it does for targets, but this would have clear disadvantages. The driving design goal was to clear obstacles as quickly as possible. Because of the limited number of sensors and the lack of memory, there is no way to know if there is an obstacle on either side of the vehicle. If there is an obstacle to the side of the vehicle, it is very likely that the vehicle has just avoided this obstacle and driven past it. This dilemma led to the design decision of wide turns for obstacles. If the vehicle passes the obstacle with a small turn, it will be very close to the obstacle when it clears it. If, instead, the vehicle passes the obstacle with a large turn, it is likely that by the next turn any forward motion from the current (large) turn will have carried the vehicle clear of the obstacle. Given the designed-in ignorance of the current system, this seems to be the best strategy. Memory of the previous positions of the obstacles and targets would allow for additional constraints in the programming.

The final issue (iii) is caused more than anything by economics. There is no inherent reason why the robot could not move more quickly. The travel time of the servo and the mechanical dynamics of the system are the fundamental speed limits of the system. These events would be measured on the order of milliseconds; the control loop computations are on the order of microseconds, with the longest portion being the analogue-to-digital conversions. The low speed of the robot was chosen for the practical reason that rebuilding it in case of a crash would not have been possible given the scope of the project. Also, the available arenas for testing would not have been able to deal with the robot moving much more quickly.

The bottom line of these results is that the system was able to exhibit seemingly complex behavior without a complex underlying system, which is very much in line with what Braitenberg suggests in *Vehicles*.

6. Summary and conclusions

Ultimately, the specific goals of the project were met. A simple system can be designed to use passive photo sensing with an apposition compound eye sensor array to achieve reasonably complex goals as inspired by certain characteristics of diurnal insects and arthropods. It should be emphasized

that the control algorithm, although hosted on a digital microcontroller, can be implemented using simple analogue operational amplifier building blocks. Future goals for this project include equipping the platform with our latest sensor array capable of hyperacuity. This will allow the vehicle to sense and avoid obstacles of much smaller dimension.

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