An Orientation Reflex for Autonomous Air Vehicles Based on a Neural Model of the Cockroach Escape Response

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Abstract: This paper investigates a biologically inspired orientation reflex for air vehicles and munitions in the endgame phase flight. The reflex is based upon an artificial neural network model of the American Cockroach's escape reflex. Guidance commands are output to a Linear Quadratic Regulator (LQR) autopilot that pilots the munition to an optimal path destination and orientation for target strike or obstacle evasion. Simulation and flight test results are presented that demonstrate the reflex's capability for aerial collision avoidance and instantaneous target strike on evasive targets, even in the presence of false or disruptive sensor data.

1 Introduction

The problem of directing a tactical missile to intercept mobile targets has been referred to as the most challenging of guidance and control problems [1]. In the classical approach, known as proportional navigation (Pronav), a controller attempts to align the velocity vector of the munition with a line-of-sight vector to its target. Even today, Pronav provides the basis for much of munition guidance and control [2].

Three fundamental phases of munition flight have been defined with respect to guidance and control [3]. These phases are commonly referred to as midcourse, terminal, and endgame stages of flight [1]. Midcourse guidance is, in effect, from the time of launch until target sensor acquisition. Once the sensors acquire the target, terminal guidance is initiated. The last second of terminal guidance is referred to as endgame. Endgame is worth treating as a separate problem since uncertainties in guidance need to be corrected much more rapidly, thrust may be unreliable due to time delay [2], and missile failure is most often associated with this phase [1].

The endgame part of intercept has received less attention in guidance and control literature than its midcourse and terminal counterparts [1]. Cottrell [4] attempted to improve end-game performance by extending classical Pronav, Dowdle et al., [5], generalized the LQG regulator, Looze et al. [6] used roll commands to compensate for target estimation error. Cho et al. [7] proposed drag minimization for missiles with non-constant velocities. Forte and Shinar [8] formulated the planar intercept as a differential game. Dougherty and Speyer [9] concluded that integrating air frame response equations is typically not feasible in real-time, and proposed pulse functions to approximate forces. It has also been noted that although non-linear models could aid in air vehicle control they are typically too large for on-board computers [1,3]. Several researchers have proposed to surmount this problem through the use of neural networks due to their capability to represent complex data in compact structures ([10] provides a brief survey).

1.1 Scope of work

In this work, a targeting/goal-acquisition reflex for autonomous air vehicles is introduced based upon a distributed network of artificial neurons that mimic the neural organization of the escape system in the American Cockroach. Although the escape response of the American Cockroach has evolved under a set of goals that are obviously different from that of a target-seeking reflex [11], extracting certain aspects of its performance nevertheless has the potential to improve endgame munition guidance. The primary deviation in functionality derives from the fact that an intercept reflex demands a specific goal point, whereas an escape response is designed to reach any position outside a threat. The nature of evasion entails an imprecision that may purposefully be integrated into escape; exact precision may result in a predictable movement observable to predators that could decrease an animal's chances for survival [11].

Despite these differences, important goals from a targeting system are consistent with those of an animal's escape response. The goal of a seeking system is to detect a target and rapidly evoke appropriate intercept maneuvers. Specifically, self-orientation, perception, decision-making, motion planning, reaction within context, and extremely rapid real-time control are all desirable and common characteristics. Finally, in addition to these criteria, an in-depth level of understanding has been achieved in mapping the cockroach escape response [19; 20] which is unprecedented in relation to similar biological mechanisms usable for autonomous control.

An endgame air-to-ground targeting scenario was selected as a case study for validation. In this scenario, a small airborne autonomous munition fires a kinetic energy projectile straight downward from its center of gravity to strike a ground target. The firing action of the munition is depicted in **Figure 1**. The task of the guidance reflex is to pilot the munition to a point where the projectile trajectory would strike target center. Note that the angular orientation of the vehicle as well as its position is critical for proper target strike. Thus, unlike the majority of munition targeting, all six degrees of freedom are relevant.

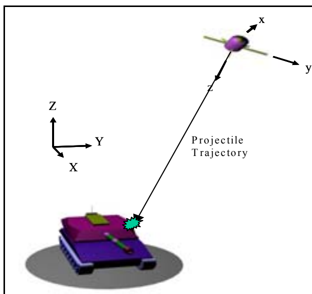

Figure 1

2 Neural Organization of the Cockroach Escape Response

The cockroach escape circuit accurately identifies air velocity gradients arising from attacking predators using mechanoreceptive hairs. This information is conducted to the thorax by ventral giant interneurons, and integrated by a network of type A thoracic interneurons (TI_A's). The TI_A's direct escape movements via both direct and indirect connections to the leg motor neurons. All of this is accomplished in approximately 60ms [11].

A reaction that considered only a singular condition would provide little adaptability to circumstance. The cockroach solves this problem by incorporating context dependence into its system. In addition to monitoring wind inputs from predators, the TI_As receive input from exteroceptive cues such as antennal contact, auditory responses, ambient light and proprioceptive cues on the state and position of the legs. The TI_As interpret the data on wind direction in the context of everything the cockroach is experiencing at the moment of the attack [11]. The context dependent nature of the escape system permits a very short reaction time because a suitable response need not be planned at the time of a particular threat, but is continuously updated based upon the animal's physiological state and environmental context.

The neural circuit that comprises the cockroach escape system has been documented by intracellular analysis and modeled on a computer as a distributed network of artificial neurons [12]. It has also been developed into a collision avoidance system for ground vehicles [13]. This work provided the basis for the expansion of the system into the guidance reflex for air vehicles presented in this paper.

3 System Overview

The general equations of motion of a 6-degree of freedom (dof) rigid airframe may be described through Newton's Laws in terms of the nomenclature enumerated in **Table 1**:

$$\tilde{F} = m\left(\frac{\partial \dot{\tilde{s}}}{\partial t} + \tilde{\omega} \times \dot{\tilde{s}}\right) \qquad \text{(1 a, b)}$$

$$\tilde{M} = \frac{\partial(\mathrm{I} \cdot \tilde{\omega})}{\partial t} + \tilde{\omega} \cdot \times (I \cdot \tilde{\omega})$$

Aerodynamic forces acting on an air vehicle, are often expressed in the form [14]:

$$\tilde{F}_A = [C_f(\tilde{z})][Q_f] \qquad \text{(2 a, b)}$$

$$\tilde{M}_A = [C_m(\tilde{z})][Q_m]$$

Where both [C] matrices are dimensionless coefficients which are functions primarily of aircraft state $\tilde{z}$ = (V, α, β, p, q, r), and each [Q] is a product of flight dynamic pressure, and aircraft reference area or characteristic length, respectively. The system inputs, u(t), include aerodynamic forces developed by actuator deflections and propulsive forces, and environmental

Variable	Parameter Description
$\tilde{F}$	Total force vector acting on airframe
$\tilde{M}$	Total moment vector acting on airframe
$\tilde{s}$	Position vector of mass center of airframe
$\tilde{\omega}$	Angular velocity of airframe (body-fixed)
m	Air vehicle mass
I	Inertia matrix of air vehicle
δe, δa, δr	Elevator, aileron, and rudder deflections
V	Absolute vehicle airspeed (global)
u	Forward velocity (body centered)
v	Side velocity (body centered)
w	Downward velocity (body centered)
α	Angle of attack=$\tan^{-1}(w/u)$
β	Sideslip angle=$\tan^{-1}(v/u)$
p	Angular roll rate
q	Angular pitch rate
r	Angular yaw rate
ψ	Roll angle
θ	Pitch angle
ϕ	Yaw angle
x_e	X position (global)
y_e	Y position (global)
H	Altitude (global)

Table 1 – Nomenclature

effects, whose impact on the air vehicle may be reflected in state space form: $\dot{\tilde{z}} = A\tilde{z} + B\tilde{u}$ (3)

For simulation testing, a flight vehicle model was extracted from [14] representing a light, single engine, high wing aircraft. This model was modified to improve responsiveness, and more closely resemble the flight characteristics of autonomous airborne munitions. Since the munition is designed to loiter over battlefields while searching for hostile targets, the air vehicle model was linearized around a steady state operating point reflecting approach to a hostile target at a cruising state. A linear quadratic regulator (LQR) autopilot was designed for this air vehicle model to execute the commands of the guidance reflex. Although the action of the autopilot could have been omitted by assuming an idealized aircraft response, testing the system with a designed autopilot will better demonstrate the utility of the guidance reflex. As with the majority of existing autopilot systems, the LQR regulator was designed to move flight control surfaces (δe, δa, δr) in response to desired roll rate (*p*), pitch rate (*q*), and yaw rate (*r*) commands [14].

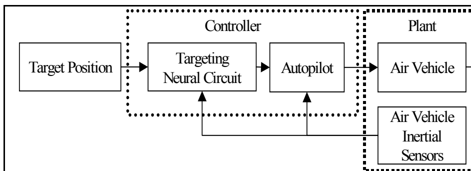

Figure 2: Control Loop

Figure 2 maps the system flow of the endgame guidance reflex and its role in on-line flight use. The position of the target as well as information on the current state of the aircraft (velocity, orientation, etc.) are provided to the endgame guidance reflex, which gives higher level commands in the form of desired roll, pitch, and yaw rates (p, q, r respectively) to a vehicle autopilot. The autopilot then manipulates aircraft control surfaces (δe, δa, δr), to achieve these commands. Altering forward thrust was determined to be not viable, since engine delay invalidates performance during endgame.

4 Insect Inspired Guidance Reflex

The proposed target-seeking circuit for autonomous munitions is shown in **Figure 3**. The architecture of this neural network is based on a model of the cockroach escape circuit [12]. Boxed labels identify functional descriptions within the aircraft target seeking reflex, while italicized text delineates the parallel structures within the cockroach escape circuit. A sigmoidal function with bias was used to model the input-output relation of a neuron. The three layers comprised functions based upon exteroceptive and proprioceptive inputs, and output commands directly to an autopilot to guide the munition to its target. It is important to note that significant alterations to the cockroach neural circuit were made for system implementation, and no claims to their biological validity are being put forth.

Although specific sensor development or processing was beyond the scope of this work, sensory structures are designed to integrate information from a variety of sources in a manner similar to that of the cockroach. Information on goal position is processed through exteroceptive structures monitoring the position of the desired target in a manner that is analogous to the insect's use of cerci. The actions of the leg sensory neurons in the cockroach escape reflex are paralleled in the guidance neural circuit through proprioceptive (inertial) sensors providing feedback on the current orientation of the vehicle, normalized with relation to flight envelope limits.

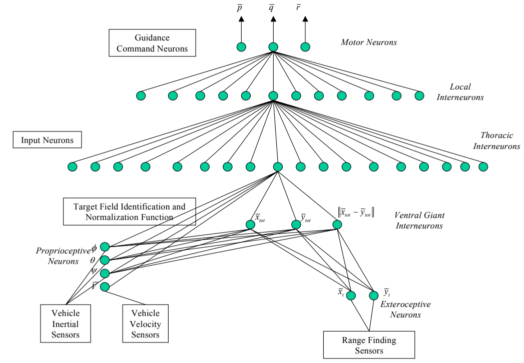

Figure 3: Guidance Neural Circuit

Although regular positional updates permit velocity information to be obtained for moving targets, the thoracic interneuron layer within the cockroach escape response utilizes information primarily associated with the current position of a threat with respect to the animal itself, and the current state of the animal. A similar approach was implemented within the target-seeking reflex.

The actions of the ventral giant interneurons (vGI) developing threat fields in the cockroach was mimicked through functions normalizing exteroceptive and proprioceptive inputs with respect to the air vehicle, and arranging these data to create a target field to be passed to the input neurons. After normalization, this output (I_{TI}) is:

$$\widetilde{I}_{TI} = (x_{tot}, y_{tot}, M_t, V, p, q, r) \qquad (4)$$

where (x_{tot}, y_{tot}) is the vector difference of the current target point of the aircraft (the strike point of the projectile trajectory shown in **Figure 1**), and M_t is the absolute distance from the strike point to the target. The munition strike point (x_t, y_t) may be represented by:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} x_e + H_f * (\tan\hat{\theta}_f \cos\hat{\psi}_f + \tan\hat{\phi}_f \sin\hat{\psi}_f) \\ y_e + H_f * (\tan\hat{\phi}_f \cos\hat{\psi}_f + \tan\hat{\theta}_f \sin\hat{\psi}_f) \end{bmatrix} \qquad (5)$$

where subscript *f* indicates states at the final point of flight and the ^ symbol represents the Euler angles transformed into angular orientations on the body centered inertial frame. Thus (x_{tot},y_{tot}) will be:

$$\begin{bmatrix} x_{tot} \\ y_{tot} \end{bmatrix} = \begin{bmatrix} x_t \\ y_t \end{bmatrix} - \widetilde{T} \qquad (6)$$

where T is a vector of the planar target position. (M_t) is simply the absolute distance from the firing point to the target point:

$$M = \left\| \begin{bmatrix} x_{tot} & y_{tot} \end{bmatrix}^T \right\| \qquad (7)$$

The quantity in the double brackets represents the Euclidean norm.

The total vector (I_{TI}), derived from Equations (5-7), represents the sum of the exteroceptive and proprioceptive inputs provided to the input neurons of the targeting reflex. These inputs are based purely on present observations; knowledge of the past will be incorporated in decisions made based upon these inputs by the trained layers within the circuit.

Eighteen neurons reside in the input (*thoracic*) layer and twelve neurons reside in the local layer. These numbers are chosen arbitrarily depending on desired performance. Each input neuron receives scaled input at the current time t. The guidance command neurons receive the message from local neurons, and output (p, q, r) commands to the autopilot. The neural network was trained using back propagation for the vehicle to respond appropriately to targeting endgame situations. System learning was confined to varying connection weights. In order to find the appropriate connection weights given the known structure of the circuit, sufficient data is needed to train this system. These data were developed from an evolutionary path planning algorithm which developed optimal intercept patterns in endgame situations for training data.

5 Generation of Training Data

Given the insect-based neural circuit, appropriate target-seeking patterns must be developed to provide training data for on-line use. Each pattern will be a "path", representing air vehicle inputs to strike a target in a certain situation; several such paths may then be used to train the neural circuit. The problem of route planning for complex vehicles may be viewed as one discrete multivariable functional optimization.

A class of heuristic searching methods based upon simulated evolution, known broadly as *Genetic Algorithms* (GAs), have recently become very popular for discrete optimization problems characterized by many local minima in nondifferentiable, discontinuous or constrained problem spaces. These evolutionary techniques are population-oriented; successive groups of feasible solutions are generated stochastically following laws similar to natural selection. This contrasts standard programming techniques that normally follow a single trajectory until a solution is reached.

Many previous path planners cannot accommodate a variety of optimization criteria or allow changes in these standards without changing the characteristics of the planner or the search map. Evolutionary approaches have this ability and are flexible to discontinuities, changes in environment, and uncertainties. For the training of the insect-based neural flight circuit an *evolutionary flight-path planning algorithm* capable of mapping paths for free-flying vehicles functioning under aerodynamic constraints is implemented. [10] details the implementation process for the evolutionary generation of targeting trajectories. In future work, this planner may function as a stand-alone trajectory generation system for all manner of air vehicles.

6 System Training

The evolutionary path planning algorithm was implemented for to generate training data for the flight neural circuit. Since the guidance reflex is designed for the endgame, distances were scaled based upon how far the simulated vehicle could travel in that time. Training situations were comprised of input and output generated per sampling time Δt, so each case gave several training patterns. Data from the target field normalization function and inertial sensors in the guidance reflex constitute the training inputs; the desired commands are the outputs of guidance command neurons from the training outputs.

6.1 Incorporation of Context Dependence

After the network was trained, the system was tested for ground vehicle strike across the targeting range. Although the reflex was capable of striking static targets with reasonable accuracy, it displayed little adaptability to moving targets. One way that the cockroach achieves adaptability to circumstance is through a context dependent shifting of its input-output weights based on the situation and environment of the animal [11]. This mechanism served as an inspiration for further training of the guidance neural circuit. Sets of synaptic connections were derived for targets located to the left of the munition, to the right of the munition, and directly in front of the munition. A simple switching strategy between these three sets of weights based upon relative target position was implemented to lend context dependent characteristics to the guidance reflex.

7 Simulation Results

After enhanced training and implementation of context-dependent weight shifting, the system was tested for both static and dynamic targets. **Figure 8** shows a typical targeting trajectory for a stationary ground target, located 32m in front of the munition. The upper plot shows the position of the ground target ('o') and the projection of the munition strike point on the ground plane for the entire flight ('x'). The global position of the plane is also plotted, and a firing trajectory is shown at the end of the flight. The targeting reflex combines the angular orientations of the aircraft such that an accurate firing trajectory is achieved with a strike point 0.67m from the target center in a 0.6 second flight. The lower plot shows the angular rate commands given by the guidance reflex versus time, and the action of the autopilot.

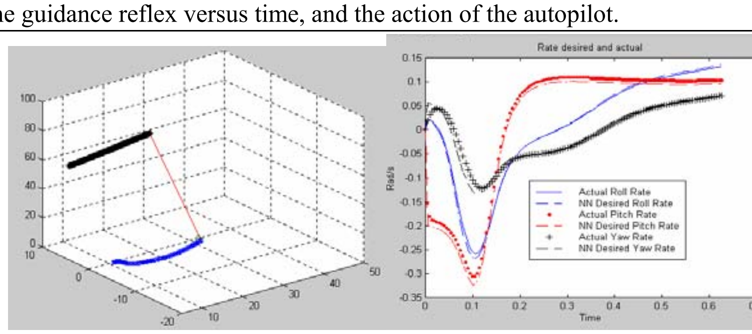

Figure 8

Although the guidance neural circuit was trained only with information on static targets, context dependent characteristics should allow for strike of mobile ground vehicles as well. **Figure 9** shows one such case, for a ground vehicle moving forward at a speed of 9.6 m/s (30% of the speed of the munition). Despite having never been exposed to a moving target, the reflex adjusts to the context of its changing environment to achieve a target strike 0.96m off center for its 0.6 second flight. Testing of this capability was performed with a target at a random location, random direction, and velocity (< 35% of the air vehicle). Over several thousand runs, 83% of the simulations resulted in a target strike. The percentage of successful strikes over several simulations will henceforth be referred to as the "target strike ratio"

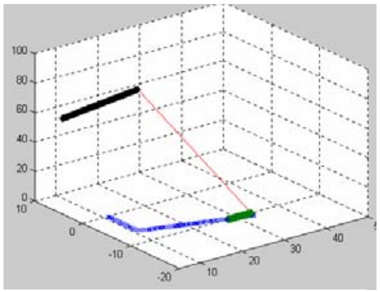

Figure 9

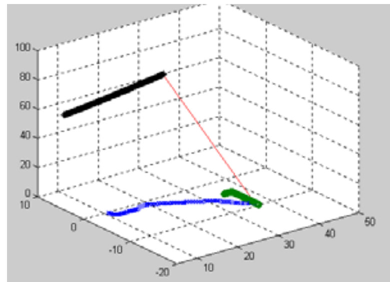

Figure 10

Performance vs. Evading Targets

In the real world, an on-line targeting system may have to deal with abrupt random changes in target path, or even analogous avoidance maneuvers. The targeting system was therefore tested in several situations when targets made sudden changes in speed and heading. **Figure 10** shows one such simulation, where a target moving 30% of the speed of the munition makes a 90° turn 0.2 seconds into the flight. The guidance reflex can be seen making adjustments to achieve a strike point 0.6 m off target center in a 0.8 second flight. The capability of the reflex to deal with changing target paths was tested again with random target placement and velocity, but with an accompanying random (90°) turn during tracking. A target strike ratio of 79% was achieved.

An acquisition system can sometimes be defeated if the target turns into the munition path to force rapid tracking without violating a flight envelope. **Figure 11** shows the target-seeking reflex responding to this escape tactic. The target begins moving perpendicular to the munition path, but upon approach, turns directly into the munition and accelerates. A target strike was achieved 1.1m away from the target center. A 73% target strike ratio was achieved with targets executing a 90° "intelligent" turn into the munition path.

Performance vs. Targets wit Sensor Disruption

As a final simulation test of the reflexive system, a ground target was given the capability to temporarily disrupt the exteroceptive sensors of the targeting system. **Figure 12** shows the results of the munition tracking a ground target capable of sensor disruption. Initially, the air vehicle receives data indicating the target is located 26 m in front of it, and 4 m to its right. As the munition approaches the target, its actual position is revealed to be 10 m in front and 8 m to the right of the perceived position. False and actual positions of the target are shown in the top figure. The guidance reflex adjusts to achieve a final strike point 0.74 m from target center. This capability was tested with a randomly placed target capable of disruption up to 10m behind and 6m to the left or right of its actual location. A 67% target strike ratio was achieved over several thousand runs.

These results demonstrate that the feasibility of implementing a neural network endgame targeting reflex for autonomous munitions based upon an insect escape circuit. Several cases for air-to-ground vehicle targeting have been successfully executed for both static and dynamic targets. The reflex is capable of directing target strike for targets moving on unpredictable paths and working through sensor disruptions. Future work involves further exploration of target escape strategies to quantify system limits, and hardware implementation on aircraft platforms.

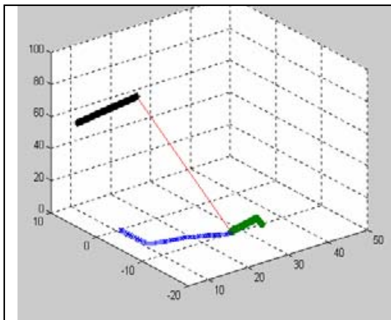

Figure 11

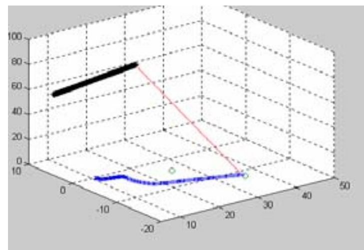

Figure 12

8 System Flight Validation

Hardware tests were performed to prove system performance under the rigor of actual flight. In addition to target-seeking, an aerial obstacle (crash) evasion reflex was implemented.

The purposes of the flight tests were to prove the capability of the reflex to successfully pilot a real aircraft through unpredictable scenarios by issuing reference signals to a rate-based autopilot. All decisions made by the neural network guidance law must be made within time-frames suitable for use on the actual aircraft. During flight tests, a test aircraft is piloted remotely along a prescribed path representing midcourse and terminal phases of flight, until the outer edge of a circular alarm region is encountered. When the plane enters this radius, it is said to be in the endgame stages of flight, and either a target seeking alarm or obstacle evasion alarm is triggered. The alarm engages an endgame control loop that relays a reference signal, provided by a neural network, to pilot the plane into or around the target. For the sake of simplicity, the actual three-dimensional flight test scenario is projected onto a two dimensional cartesian grid. The goal of the plane was to strike (collide with) or evade a virtual aerial target. Also, for the simplified flight vehicle, the thoracic layer of hidden neurons in the neural circuit was severed. Finally, the full implementation of the genetic algorithm was not necessary for the generation of training data; kinematic data alone was used. Also note that the aircraft is not equipped with targeting sensors, but is fed an initial target relative position which it updates based upon inertial feedback.

Hardware System Overview

The hardware system consists of a 1/4 scale Piper J-3 Cub aircraft, a transmitter, receivers, control surface servos, a dynamic (inertial) measurement unit (DMU) a set of wireless modems, and a ground based computer. The 1/4 scale Cub is a high wing monoplane with a wingspan of 108 inches, a wing area of 1,610 inches^2, and a length of about 68 inches. The engine has a displacement of 2.1inches^3 (35cc), spins a 20x8 prop, and has a cruising speed of 30-35mph. With the DMU installed, the entire plane has a wet weight of 30 lb. The upper left portion of **Figure 13** shows the test plane constructed.

The transmitter has an internal computer that enables a human pilot (flying the plane through joysticks remotely) to mimic midcourse and terminal phases of flight. The computer then assumes control during endgame (when the plane enters the target "alarm" radius).

This experimental setup is chosen because of its flexibility. Note that the ground computer contains the entire controller portion of the loop, and can be modified while the plane is in the air. The autopilot used in these experiments is an open loop controller designed to move flight control surfaces (δe, δa, δr) in response to desired roll rate (p), pitch rate (q), and yaw rate (r) commands. Altering forward thrust is not viable since unpredictable engine delays are difficult to model. Flight tests were performed with an alarm radius of 30m.

Flight Implementation Results

Figure 14 shows typical flight responses from targeting and evasion neural networks, projected onto a two dimensional Cartesian grid. Figures show graphs of actual plane path data. Note that the z-axis is always pointing downward, and the coordinate system is right handed. Inside the alarm radius, represented by the large circle, the targeting or evasion neural network is engaged to react to a stationary virtual pole.

Since target-seeking is a more formidable problem than target evasion, several typical target seeking responses are shown. In all of flight results shown, the planned course is along the x-axis of the figure, and the plane is flying in the positive x direction. In these examples, the terminal guidance controller uses servo limits that correspond to half of maximum control surface excursion, so it cannot track a heading perfectly. This is desirable because it forces the plane to enter the alarm radius at unpredictable orientations. Therefore, the neural network is subjected to more rigorous tests. Note that in most flight tests, the terminal controller cannot compensate for

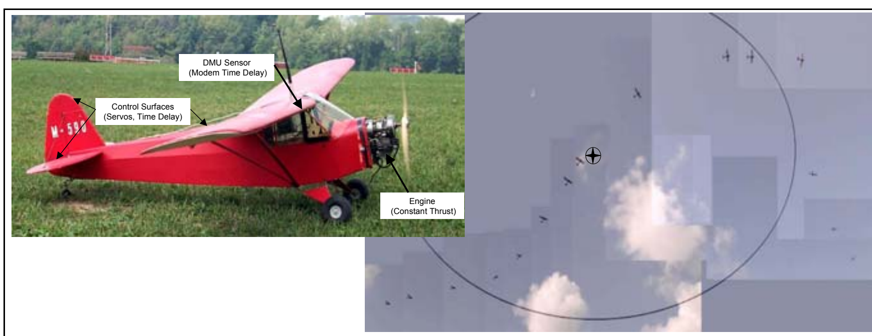

Figure 13: (left) ¼ Scale Piper Cub Test Platform; (right)Actual flight trace of aircraft moving into alarm radius, striking virtual target, holding heading until exiting alarm radius, and resuming original flight path, corresponding to **Figure 14D**

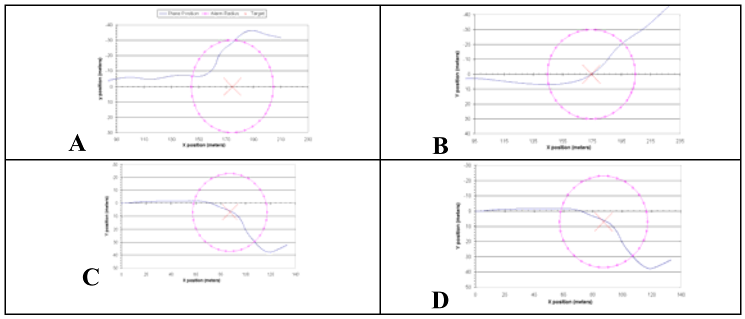

Figure 14: Evasion (A) and Targeting (B, C, D) responses from flight testing of 1/4 scale Piper Cub. Note: the z-axis is pointing into page.

wind, and plane is being blown toward the right or left of the desired x-axis path.

In **Figure 14A**, the terminal guidance controller is fighting wind, which is pushing the plane to the left of the x-axis (off course). Therefore, the plane enters the alarm radius in a shallow right turn that terminal guidance system has initiated, in an attempt to track the x-axis. The reflex immediately throws the control surfaces to bank the plane left and the plane turns smoothly away from the target. The neural network then tries to fly around the object, but momentum carries it out of the alarm radius. Once outside the alarm radius, terminal guidance turns the plane right to again track the x-axis. **Figure 14B** shows a targeting scenario where the plane has been blown off course to the right, and the target is located on the x-axis. The neural controller is able to overcome the wind and smoothly cut leftward, into the target that resides on the x-axis. In all targeting scenarios, once the neural controller has hit the target, it seeks to track the global heading achieved at impact and fly out of the alarm radius. Note that terminal guidance does not push the plane back toward the x-axis because that command would have flown the plane out of the allowed airspace. A human pilot took control shortly after the plane exited the alarm radius. **Figure 14C** shows the plane being blown off course, and oriented away from the target when it meets the edge of the alarm radius. The neural controller turns the plane leftward, hits the target, and maintains the heading attained at virtual impact. **Figure 14D** shows a scenario similar to **Figure 14C** but the target is offset to the right of the x-axis. The plane strikes the target, holds a heading, and flies out of the alarm radius.

Figure 13 (right side) shows the actual flight corresponding to the trace shown in **Figure 14D**. Images were taken with a digital video camera, stills were extracted, and a composite was created. The action of the plane moving towards the target upon entering the alarm radius, flying through the goal point (target), and resuming the original path can clearly be seen in the figure.

During all flights, the neural network is robust to sensor noise, unpredictable transmission delays, and dropped data packets. The major hindrances of using a control computer on the ground are the time delay incurred in wireless modem transfer, and the increase in software complexity. The neural network successfully compensates for these additional constraints during flight-testing.

9 Conclusions

The results presented demonstrate the feasibility of implementing an insect-based control circuit for reflexive flight control. The performance of the system has been proven in both simulation and flight. It is capable of striking static and maneuvering threats, taking evasive action in the presence of false or disruptive sensor data, and operating at frequencies suitable for an endgame controller.

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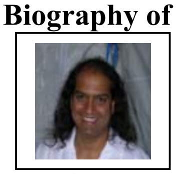
Biography of Authors



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