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An Insect-Inspired Endgame Targeting Reflex for Autonomous Munitions

Ravi Vaidyanathan[1,2*], Roger D. Quinn[2], Roy E. Ritzmann[3], Troy S. Prince[1]
[1]Orbital Research Inc., Cleveland, OH, USA
[2]Department of Mechanical Engineering, Case Western Reserve University, Cleveland OH, USA
[3]Department of Biology, Case Western Reserve University, Cleveland OH, USA

Abstract

A target-seeking system for autonomous munitions in the endgame stage of flight is developed based upon a neural network model of the cockroach escape reflex. Despite significant differences in objectives, certain aspects of the cockroach escape response are consistent with desired characteristics of a target seeking system. An evolutionary target-seeking algorithm was generated to gather data to train the neural net target-seeking system. Targeting data was generated through intensive off-line computing, which the target-seeking reflex was trained to reproduce on-line instantly. A linear quadratic regulator (LQR) autopilot executes reflexive guidance commands. With the trained target-seeking system installed on a candidate air-to-ground munition, simulations show that the reflex may react to strike targets very quickly. Context dependency was demonstrated through the actions of the reflex striking targets moving on rapidly changing, evading, and unpredictable trajectories, as well as through false and disruptive sensor data.

I. Background

The problem of directing a tactical missile to intercept mobile targets may be the most challenging of all guidance and control problems [1]. In the classical approach, referred to as proportional navigation (Pronav), a controller attempts to align the velocity vector of the munition with a line-of-sight vector to its target [2]. Even today, Pronav provides the basis for the majority of munition guidance and control[3; 4].

With regard to guidance laws such as Pronav, three fundamental phases of munition flight have been defined [5]. These phases are commonly referred to as midcourse, terminal, and endgame stages of flight. 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, and thrust may be unreliable during this final phase due to time delay [3]. Evasive maneuvers, sensor disruptions, and random target or environmental fluctuations thus stand the best probability of defeating the guidance system if utilized during this flight stage [1].

The endgame part of intercept has received less attention in guidance and control literature than its midcourse and terminal counterparts. Cloutier, et. al. reported [1], “It is disappointing that the endgame stage of guidance has not received more attention since the deficiencies in missile kill effectiveness are associated primarily with this portion of the intercept.” In early work, Cottrell [6] attempted to improve end-game performance by extending classical Pronav to incorporate additional features in the system model. Dowdle et al., [7; 8], generalized the LQG regulator for endgame guidance. Looze et al. [9] found that target estimation was used poorly by Pronav, and compensated with roll commands to improve miss-distance performance. Cho et al. [10] observed that Pronav is not accurate for munitions with non-constant velocity profiles, and proposed optimal guidance based on drag minimization. In a departure from these approaches, Forte and Shinar [11,12] formulated a planar intercept problem as a mixed-strategy, zero-sum, stochastic differential game. With respect to an integrated approach for all flight phases, Kumar et al. [3] reported that the lack of engine thrust (due to delay) during endgame reduces controllability, and showed that Pronav may be implemented for endgame given an aligned collision course, little error, and very short time to go. In another study, Dougherty and Speyer [13] concluded that integrating air frame response equations is normally not feasible in real-time, and proposed using narrow pulse functions to approximate forces in guidance law development.

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]. Motivated by the goal of improving flight system performance several researchers have proposed neural networks for aircraft due to their capability to represent complex data in a compact structure for fast throughput [14; 15; 16; 17; 18;]. Neural networks hold great promise for use in endgame munition guidance due to this capacity.

II Introduction

In this paper, a targeting/goal-acquisition reflex for autonomous air vehicles is developed based upon a distributed network of artificial neurons that mimic the neural organization of the escape system

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
$\tilde{\varpi}$	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

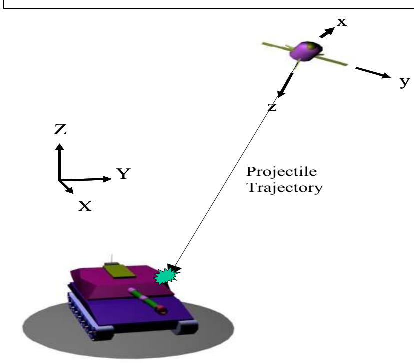


Figure 1

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 [19], extracting certain aspects of its performance nevertheless has the potential to improve endgame munition guidance. The primary deviation in functionality between an intercept and escape response lies in the fact that the intercept problem is an inversion of escape goals – an intercept reflex demands a specific goal point while an escape response is designed to reach any point outside of a threat. The open nature of evasion has led to a level of 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 [19]. Such characteristics would hinder an intercept reflex, where endpoint position is critical.

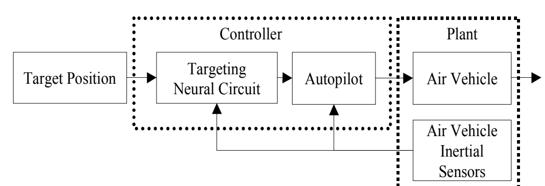


Figure 2

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 faithfully detect a target from numerous stimuli, and evoke appropriate intercept maneuvers within the context of the vehicle's internal state and external environment. The system must do all of

* corresponding author: rxv@po.cwru.edu

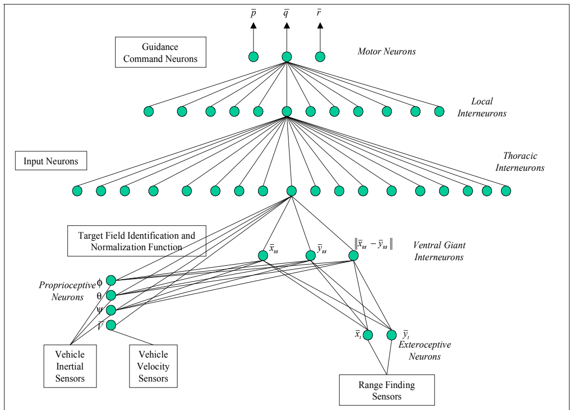


Figure 3: Guidance Neural Circuit

this in a very short period of time. Specifically, self-orientation, perception, decision-making, motion planning, reaction within context, and extremely rapid real-time control are all shared characteristics. Extracting these features would provide benefit to autonomous munition guidance. 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. These factors provided the motivation in selecting the cockroach escape response as the inspiration for an endgame target-seeking reflex.

As a case study for demonstration of the reflex, an air-to-ground targeting scenario during the endgame stage of flight was chosen. 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**, with global and body fixed reference frames delineated, along with the projectile trajectory. The task of the guidance reflex was to pilot the munition to a point where the projectile trajectory would strike as near as possible to the 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 where only global position at strike is relevant, this problem requires all three translational and all three rotational degrees of freedom of the vehicle to be optimized.

III. Neural Organization of Cockroach Escape Response

The cockroach escape circuit accurately identifies rapidly accelerating wind stimuli as arising from predators. Wind information is gathered by mechanoreceptive hairs and is conducted to the thorax by ventral giant interneurons. There it is integrated by a distributed population of interneurons, called type A thoracic interneurons (TI_A's). The TI_A's direct turning movements away from the lunging predator via both direct and indirect connections to the leg motor neurons. All of this is accomplished in approximately 60ms [19].

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 distributed network of TI_As interprets the data on wind direction in the context of everything the cockroach is experiencing at the moment of the attack [19]. 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 [20]. It has also been developed into a collision avoidance system for ground vehicles [21]. This past work provided the basis for the expansion of the system into the guidance reflex for autonomous munitions presented in this paper.

IV 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**:

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

Aerodynamic forces acting on an air vehicle, are often expressed in the form [22]:

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

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

* corresponding author: rxv@po.cwru.edu

developed by actuator deflections and propulsive forces, and environmental effects, whose impact on the air vehicle may be reflected in state space form:

$$\dot{\tilde{z}} = A\tilde{z} + B\tilde{u} \quad (3)$$

For simulation testing, a flight vehicle model was extracted from [23] representing a DHC-2 Beaver; 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 developed 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 [22].

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 is not viable since engine delay invalidates performance during endgame.

V. 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 [20]. 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 is used to model the input-output relation of a neuron. The three layers comprised function 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[i] 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.

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:

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

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:

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

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:

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

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

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

[i] The simulated vehicle was equipped with a LADAR sensing array [24]

* corresponding author: rxv@po.cwru.edu

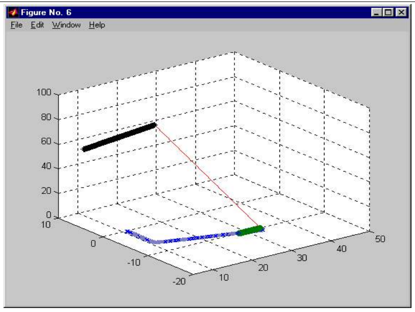


Figure 5

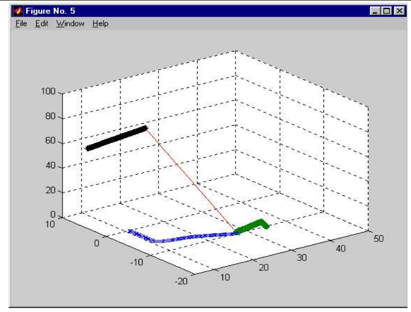
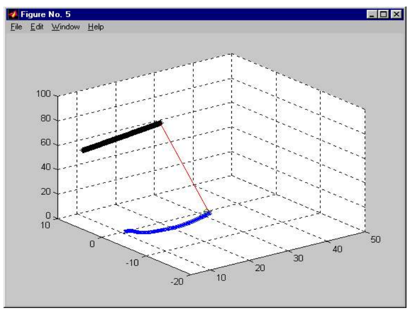


Figure 7

where 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 the 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 to make the vehicle respond appropriately to

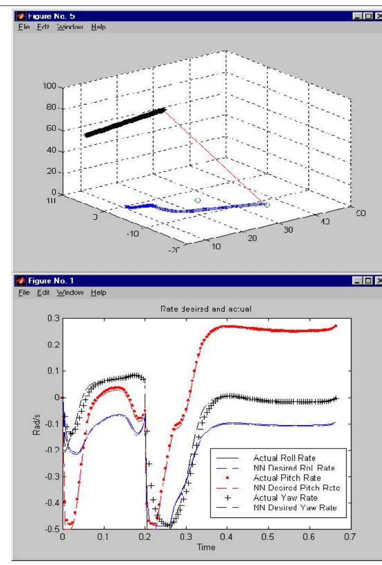


Figure 8

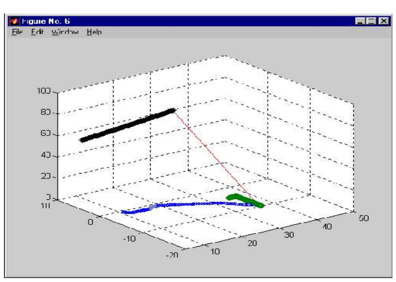


Figure 6

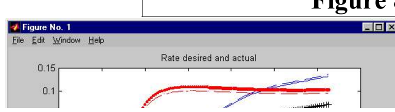


Figure 4

* corresponding author: rxv@po.cwru.edu

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.

VI. System Training

Generation of Training Data

The initial conditions of the simulated munition were its steady-state response [24]: V=32 m/s; α=0.1443 rad; β=-0.18 rad; p=0 rad; q=0.144 rad; r=0 rad; ψ=0 rad/s; θ=0 rad/s; ϕ=0 rad/s; x=0 m; y=0 m; H=75 m. The flight envelope limits were: V_{min}=20 m/s; α_{max}=0.52 rad; α_{min}=-0.18 rad; β_{max}=0.3 rad; β_{min}=0.3 rad; p_{max}=0.5rad/s; p_{min}=-0.5 rad/s; q_{max}=0.5 rad/s; q_{min}=-0.5 rad/s; r_{max}=0.5 rad/s; r_{min}=-0.5 rad/s; ψ_{max}=0.5235 rad; ψ_{min} =-0.5235 rad; θ_{max}=0.3141 rad; θ_{min}=-0.15 rad; H_{min}=20 m.

Target seeking patterns were prepared using an evolutionary path planning algorithm (described in [25; 26]) to train the neural network. Vehicle flight constraints, path destination, and final orientation were optimized through fitness evaluation and iterative improvement of generations of candidate flight paths. Evolutionary operators comprised of one crossover operation and six mutation operators. Although the purpose of the path planner was to pilot the vehicle to strike as close as possible to the specified target point, a strike within 3m (the approximate size of a military ground target) of that point was considered a hit. Thus the path was optimized not only to simply strike the target, but to hit as close as possible to its exact center.

Since the guidance reflex is designed for the endgame, distances were scaled based upon how far the simulated vehicle could travel in that time. A range of 15m to 40m in front of the vehicle, 5m to the left of the vehicle and 15m to the right was selected for endgame targeting actions[ii]. 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.

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 the animal is in [19]. 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.

VII. Simulation Results

General Performance

After enhanced training and implementation of context-dependent weight shifting, the system was tested for both static and dynamic targets. **Figure 4** shows the 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 in executing them.

Although the guidance neural circuit was trained only with information on static targets, context dependent characteristics should allow–strike of mobile ground vehicles as well. **Figure 5** 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, given a random direction and velocity (up to 35% of the air vehicle). Over several hundred runs, 83% of the simulations resulted in a target strike.

Performance versus 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 6** shows one such simulation, where a target moving

[ii] In steady state, the vehicle has a right side slip (β<0); hence the larger target range in this direction

* corresponding author: rxv@po.cwru.edu

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.

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 7** 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. The capability of the reflex to deal with changing target paths was tested with random target placement and velocity, accompanied by a 90° turn during tracking. A 79% target strike ratio was achieved over several hundred runs.

Performance versus Targets with Sensor Disruption

As a final test of the reflexive system, a ground target was given the capability to temporarily disrupt the exteroceptive sensors of the targeting system. **Figure 8** 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. Commands of the reflex and autopilot execution is also shown. 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[iii]. A 67% target strike ratio was achieved over several thousand runs.

VIII. Conclusions

The results presented in **Section VII** 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.

[iii] It is assumed the munition achieves more accurate data as it nears the target, thus a false position in front of actual location was not possible.

Acknowledgements

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* corresponding author: rxv@po.cwru.edu