A Contrast-Based Neural Control System for Ant Navigation

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A mathematical model for a neural control system of ant locomotion was developed. Contrast-based detectors using excitation and inhibition were tuned to specific contrast orientations. A control system using multiple orientation contrast detectors was then developed and optimized for a model ant, which could move via a biased random walk. The system allowed sufficient control to guide the ant through various mazes.

KEYWORDS: Ant, Contrast, Excitation, Inhibition, Synchrony

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INTRODUCTION

Ants use pheromone trails to navigate between their colonies and food. They have a ventral nervous system and use specialized sensory receptors on their antennae to detect pheromone. Neurons in the central part of the brain use the inputs from these sensory neurons to determine the presence or absence of pheromone as well as concentration profiles. In addition to pheromones some ants use a combination of peripheral and dorsal visual contrast cues for orientation, including contrast in the polarity of light (Labhart and Meyer, 2002). We suspect that the more advanced contrast-based mechanisms of control that ants use may have interesting properties not found in other animals. Bees for example are known to store distance information as a function of visual flux. A bee's sense of distance traveled can be, therefore, thrown off by changes in the path. Labhart and Meyer (2002) suggest that unlike bees, ants may use internal clocking devices which allow more robust sense of distance. One reason for this development may be that the flight path of bees can be held relatively constant for long distances while ants must negotiate and climb over large obstacles.

Therefore, it was investigated if a reasonable neural basis for contrast detection could be developed which could guide ant movement. Ant navigation through a characteristically difficult and evolving environment requires a highly complex neural system (Koch and Laurent, 1999). In this project we approach this problem by designing a simplified model of a two-dimensional (2D) ant containing an artificial neural network (Garliauskas, 2003) of sensory and processing neurons. Furthermore, the environment, or "context" (Caticha et al., 2002), is taken to be a 2D field with periodic boundary conditions, containing a static array of binary inputs.

METHODS

Neural processes

The equations used to model the neural network of the ant's sensory periphery and cognition are based on a variant of the Fitzhugh-Nagumo equation (Fitzhugh, 1965) coupled with a scaled hyperbolic tangent dependence of the membrane potential (Terman, 1995). These equations model membrane voltage, voltage gated ion channel dynamics, and active synaptic connections. Therefore, the approach taken to model the neurons, albeit abstract, is based in biological reality. Specifically, the system of differential equations used was,

$$\begin{aligned} \frac{dV}{dt} &= 3V - V^3 + 2 - X + I \\ &\quad + J'\left[Gsyn \bullet * S \bullet * \left(Vsyn - Vdst\right)\right] \\ \frac{dX}{dt} &= \varepsilon\left\{\gamma\left[1 + \tanh\left(\frac{V}{\beta}\right)\right] - X\right\} \\ \frac{dS}{dt} &= \sigma(Vsrc) \bullet * \left(1 - S\right) - S \end{aligned} \qquad 1.$$

where,

$$\sigma(z) = \frac{1}{1 + e^{\frac{-(z-\theta)}{\kappa}}} \qquad 2.$$

In this model, V is a 1xN vector of neuron membrane potentials, X is a 1xN vector that represents the combined action of various voltage-gated ion channels (e.g. sodium, potassium), I is an exogenous input (assumed to be zero except for neurons in the sensory periphery), J is an Nx1 vector of ones. $Gsyn$ is a NxN matrix where the ith,j^{th} entry represents the synaptic weight (conductance) of the synapse of the axonal projection of neuron i and dendritic projection of neuron j. Similarly, S is an NxN matrix representing postsynaptic neurotransmitter concentrations and $Vsyn$ is an NxN matrix carrying the synaptic reversal potentials at the synapse of neurons I and j. $Vsrc$ is the Kronecker product of V and J, and therefore represents the voltage of the pre-synaptic neuron while $Vdst$ is its transpose and represents the voltage of the post-synaptic neuron B,ε,κ, and θ, are tunable parameters which adjust the frequency and sharpness of voltage

spikes. The operator ●* represents "element-by-element" multiplication ($A●*B = C$: $C_{i,j} = A_{i,j}*B_{i,j}$).

We created a modular contrast detector in which multiple sensory neurons (SN) synapse onto a single "integrating" neuron (IN). Each SN was designed to send either inhibitory or excitatory inputs to the IN. By modifying the relative spatial location of these excitatory and inhibitory SN, the specificity of each module could be tuned to a particular contrast orientation (see Fig.1). Weakly excitatory nearest-neighbor coupling among the SN was required to maintain synchronicity of firing while both populations of SN sent excitatory inputs to the IN.

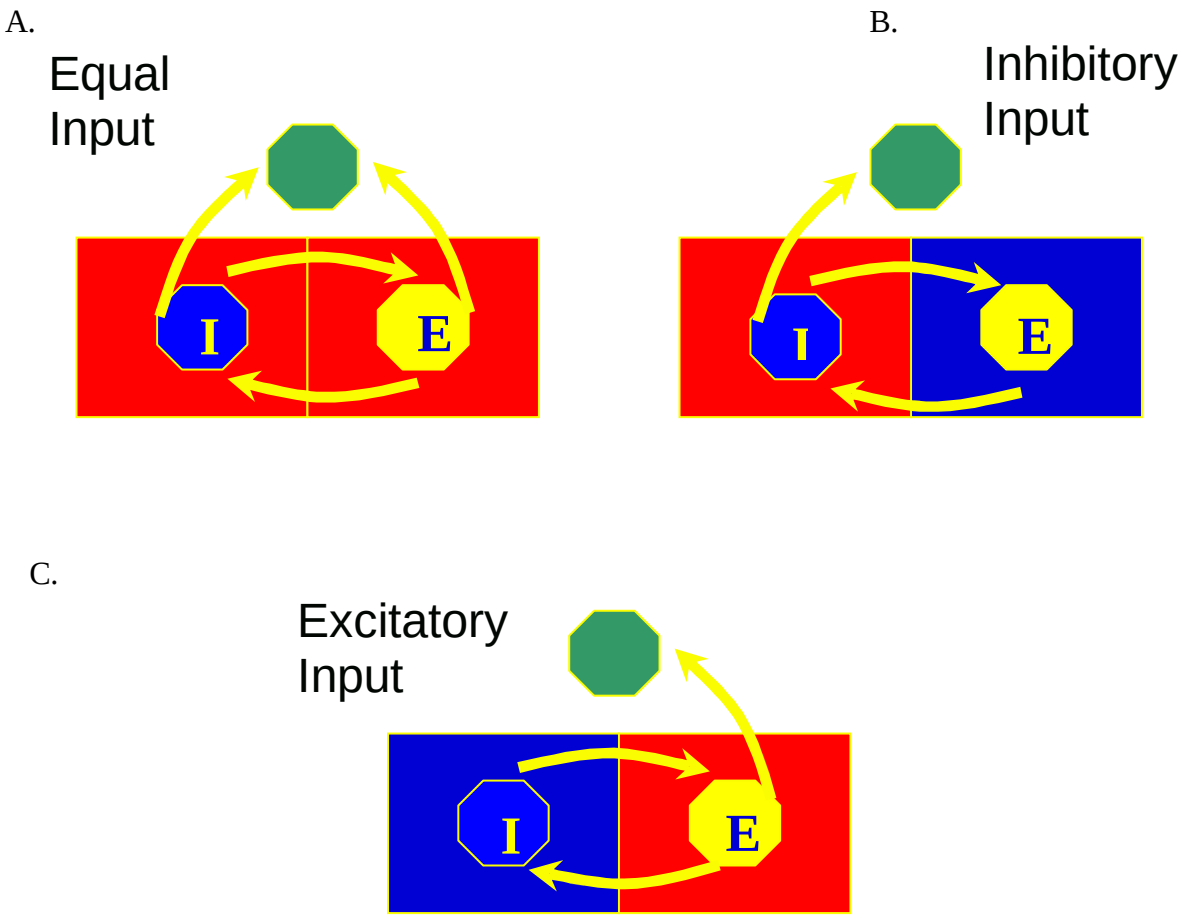

Figure1: Contrast detector functionality for background trail (blue square) and in presence of pheromone (red square). The E neuron excites IN in the presence of pheromone while the I neuron inhibits IN in the presence of pheromone. A) Both the excitatory and inhibitory cells receive input from the path. The excitatory input to IN from E is balanced by inhibitory input from I and IN does not fire. B) Only the inhibitory neuron receives exogenous input so the IN is only receiving inhibitory input and it should not fire. C) Only the excitatory neuron is receiving exogenous input and so the IN receives more excitatory than inhibitory input and so it should fire.

Motion

In the absence of sufficiently strong contrast cues ants tend to move at random (Ehmer, 1999). We, however, assume that the ant's movement may be biased as a function of sensory inputs. Therefore, we model the ant's position as an Ornstein-Uhlenbeck process. Specifically the ants position (a, b) is governed by the differential equations,

$$\begin{aligned} \frac{da}{dt} &= v_a * D_a + \delta * W(dt) \\ \frac{db}{dt} &= v_b * D_b + \delta * W(dt) \end{aligned} \qquad 3.$$

where v_a and v_b are the velocities in the *a* and *b* direction, $[D_a, D_b]$ is a unit vector specifying orientation of the ant's body, δ is a constant whose magnitude reflects the velocity due to random diffusion and *W(dt)* is a Wiener process (Medhi, 1982 pp. 147-149). Using this model, the ant's movement has a certain direction and velocity, but also has noise added.

After the ant detects contrast, it moves away from that contrast: away from the edge and back onto the trail. We used a linear rotator to change the direction vector of the ant (Fig. 2).

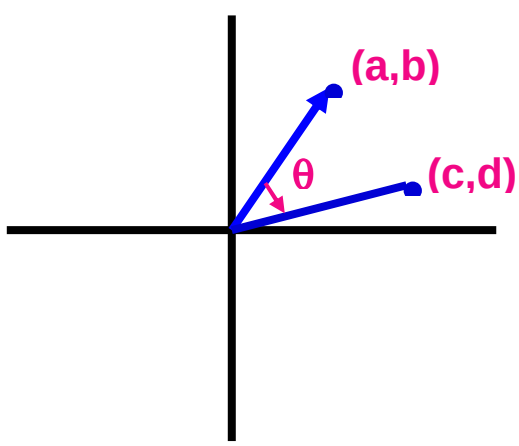

Figure 2: The ant whose direction vector is (a, b) changes to direction (c, d)

If the ant originally has a direction vector of (a, b) the new direction (c, d), is determined by

$$\begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} c \\ d \end{bmatrix} + noise \qquad 4.$$

Continuous control

The ant's contrast-based neural control system was challenged with three trails. These included a circular trail, a T-maze and a complex trail (see Fig. 3). The boundaries of each maze were assumed to be toroidal. In order to approximate continuous sensory perception and locomotary response, a fractional step method was employed (Press et al, 1992 pp. 847-848) . Specifically, the equations 1 were solved for a small time *dt/2*. The spike frequency of the IN determined which locomotary behavior the ant would exhibit (see Fig. 4). Then for time *dt/2* the Ornstein-Uhlenbeck equations were solved. Thus, the position and neuronal state of the ant could be simulated with temporal resolution *dt*.

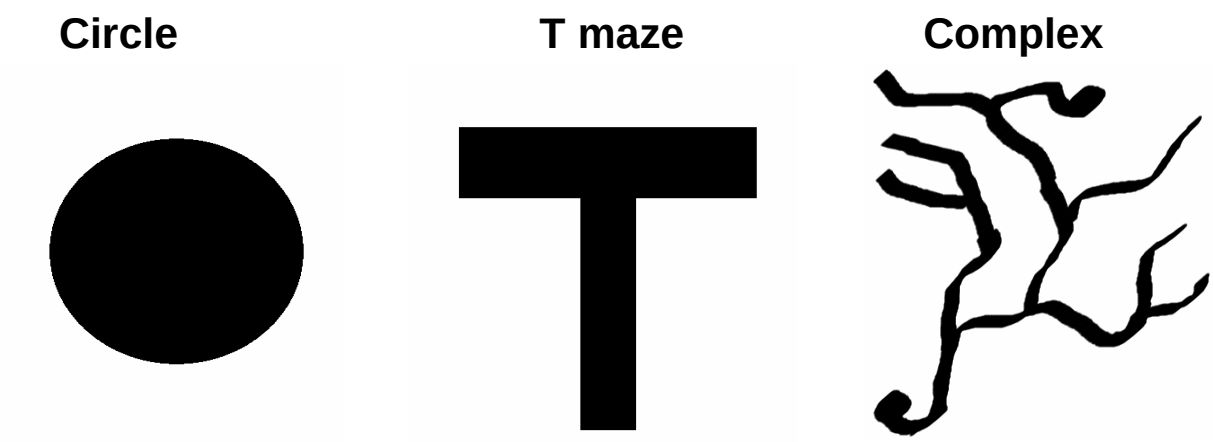

Figure 3: The three trails used to challenge the neural control system.

RESULTS

We found heightened neural control using a 4 module sensory network capable of detecting contrast in 4 cardinal directions (see Fig. 5). Furthermore, adding multiple SN in each module increased robustness. In the final design, each module consisted of 8

excitatory neurons and 8 inhibitory neurons. With this setup, the ant was more likely to detect an edge and also more likely to detect an edge with noisy input. The final network is shown in Figure 4. Each of the 16 SN contrast detectors were linked to an IN. If the IN fired (i.e. its membrane potential increased across zero), the ant would move in the reverse direction of the module's orientation of specificity.

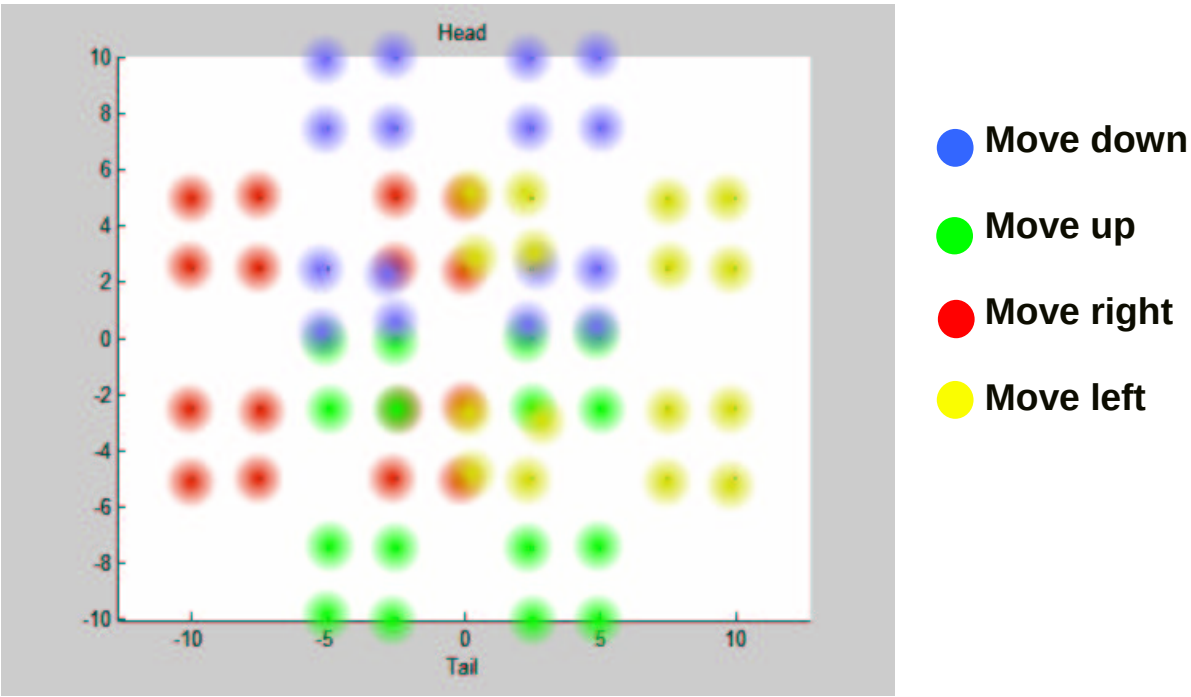

Figure 4: The spatial arrangement of the sensory network. Each set of colored spots represents a separate contrast detector. The colors indicate the contrast orientation specificity of each detector.

We found that modules with no coupling among SN neurons would function properly under constant stimulus scenarios. This phenomenon is likely due to the small locus of attraction provided by the coupled oscillators in 1. However, the SN would become de-synchronized or fire out-of-phase during movement across variations in sensory stimulus. To obviate this problem the SN within a particular module were linked together with nearest-neighbor excitatory connections (see Fig. 6). These connections synchronized SN, input to the IN.

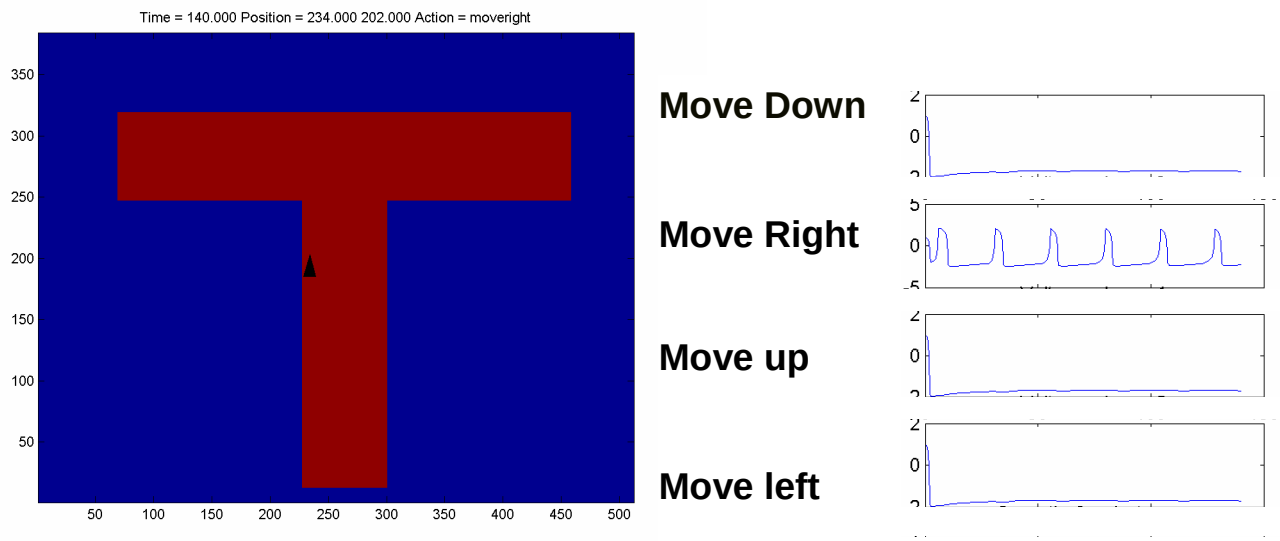

Figure 5: An edge detector at work. The ant is on the left edge of the maze with contrast only in the left direction. The Move Right integrator is the only IN firing while the other 3 IN experience transient low levels of excitation.

Determination of model parameters

Since detailed data on ant movement in trails such as those shown in Fig. 3 were not available, the model parameters were tuned primarily by trial-and-error. However, an important preliminary calculation was made to determine the largest rate of sensory transition possible in one step. Specifically the quantity $\max(v_a, v_b)\frac{dt}{E}$ was determined where E is the minimum width of a trail. To be able to detect an edge, the sensory network was set up so that the inhibitory and excitatory neurons were far enough away from each other so that when the ant moved, only the inhibitory detectors would fall off the path and not the entire contrast detector. Furthermore, we found that the ant was likely to stay on the path if the contra lateral movements were accompanied by small rotation. For rotation angles used see Table 1.

Table 1: Angles of rotation implemented for each of the four possible locomotary actions.

Direction	Move Left	Move Right	Move Up	Move Down
Angle	30 degrees	-30 degrees	15 degrees	15 degrees

Additionally, the ant was positioned in 4 constant contrast scenarios to identify optimal spiking of the corresponding IN. Specifically, the synaptic resting potentials (*Vsyn*) were

varied for the three types of connections (excitatory to IN, inhibitory to IN and nearest neighbor SN) until the contrast detector worked specifically for its orientation (Fig 5). The values for *Vsyn* that we found effective are given in Table 2.

Table 2: Synaptic resting potentials found to confer contrast orientation specificity to the 4 IN neurons. Note that positive values of Vsyn correspond to excitatory synaptic input while negative values correspond to inhibitory synaptic input.

Synaptic Connection Type	*Vsyn* Value
Excitatory to IN	35
Inhibitory to IN	-40
Excitatory Nearest Neighbor	10

In contrast, the conductances or synaptic weights *Gsyn* did not require extensive tuning. The value of *Gsyn* was set to 1 if there was a connection and was 0 if there was no connection between the neurons. The values determined for the tunable parameters in Eqn. 1 were determined during similar trial scenarios and are given in Table 3.

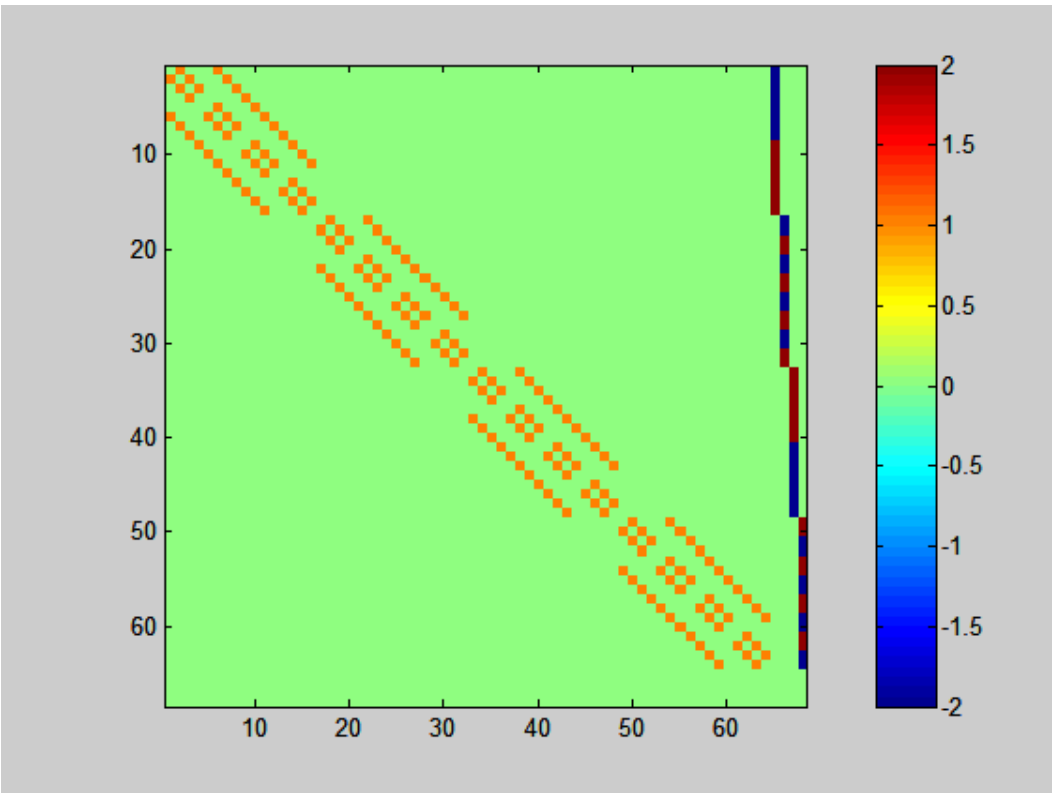

Figure 6: This 68x68 matrix represents the synaptic connections of the 68 neurons in the network. The ith,j^{th} element represents the synaptic strength for pre-synaptic neuron *i* and post-synaptic neuron *j*. The first 64 neurons are sensory neurons while the last 4 are the integrator neurons. Negative strengths correspond to inhibitory neurons.

Table 3: Model parameter values used in simulation studies.

Parameter	Description	Value
γ	Scales relative rates of channel opening to channel closing	25
ε	Scales relative rate of channel dynamics to voltage dynamics	0.04
β	Controls rate of channel opening (steepness of hyperbolic tangent)	1
Θ	Pre-synaptic voltage at which half of channels are open	1
κ	Channel sensitivity to pre-synaptic voltage	0.5
ν_x, ν_y	Velocity the bug moves in the x and y directions	0.2
δ	Velocity due to random diffusion	0.2

CONCLUSION

Ants use the contrast found in various forms of stimuli to navigate through their environment. Although both the environment (context) and the ant's neural network are very complex in the dynamics and design (Koch and Laurent, 1999) we have created a simple model of a computational ant that exhibits basic sensor-motor control in a static 2D environment. This model illustrates several sensory and motor design principles that are likely to be important in the navigation of an actual ant in the real world. Specifically, we have demonstrated how sensory modules must have receptive fields that are spatially separated in order to detect contrast during motion. The separation of these modules as well as the strengths of excitatory and inhibitory synaptic connections must be tuned in concert in order to achieve acceptable orientation specificity.

Future work will be focused on developing more realistic representations of the neural systems as well as of the ant environment. Specifically, we would like to achieve a closer matching of the turning statistics of ants in the presence of concerted and contrasting stimuli. This would involve, for example, tuning attention to simultaneous visual and and pheromone stimuli. Under some conditions the stimuli could reinforce each other while other scenarios could involve conflicting stimuli. Another possibility would involve dynamic shifts in these stimuli. Pheromone trails, for example, are known to dissipate over time. One way of accomplishing navigation under such conditions within the context of the current modeling framework would be to modulate *Gsyn* values in response to the stimuli. Furthermore, the long range navigation and homing capabilities of ants are thought to involve a process of distance tracking called path integration. In order to incorporate path integration, learning and memory capabilities will be added to the neural model. Such mechanisms may allow an ant to associate gradients in the stimulus with spatial regions of the environment. With the addition of these computational complexities we expect there will be an increase in the computational burden. In the current model, for instance, we used 68 neurons, giving a total of 344 simultaneous differential equations to solve each time step. Through balancing the computational complexity with the known neurophysiology we hope to develop

capabilities sufficient to allow the simulation of biologically realistic neural control mechanisms in complex environments.

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