2014 IEEE World Congress on Computational Intelligence (WCCI)
06 Jul - 11 Jul 2014, Beijing, China

Mimicking the worm – an adaptive spiking neural network for contour tracking inspired by C. Elegans thermotaxis

Ashish Bora, Arjun Rao, Bipin Rajendran
Dept. of Electrical Engineering, Indian Institute of Technology, Bombay, India

Introduction

- A widely studied model organism , nematode C. Elegans, can track regions with constant temperatures or chemical concentrations.
- A nearly complete structure and connectivity of the neural network of C. Elegans has been known for two decades.
- However there have been no neural models that completely and quantitatively explain non-trivial behaviors such as thermotaxis arising from basic neural networks.
- We demonstrate a spiking neural circuit inspired by the architecture of the network believed to control thermotaxis in C. Elegans.
- We quantify the performance of our model for discovering and tracking contours, in terms of accuracy and energy efficiency.

Model for Spiking Neurons and Synapses

$$C\frac{dV(t)}{dt} = -g_L\left(V(t)-E_L\right)+g_L\Delta_T\exp\left(\frac{V(t)-V_T}{\Delta_T}\right)-U(t)+I_{app}(t)+I_{syn}(t)$$

$$\tau_w\frac{dU(t)}{dt} = a\left[V(t)-E_L\right]-U(t)$$

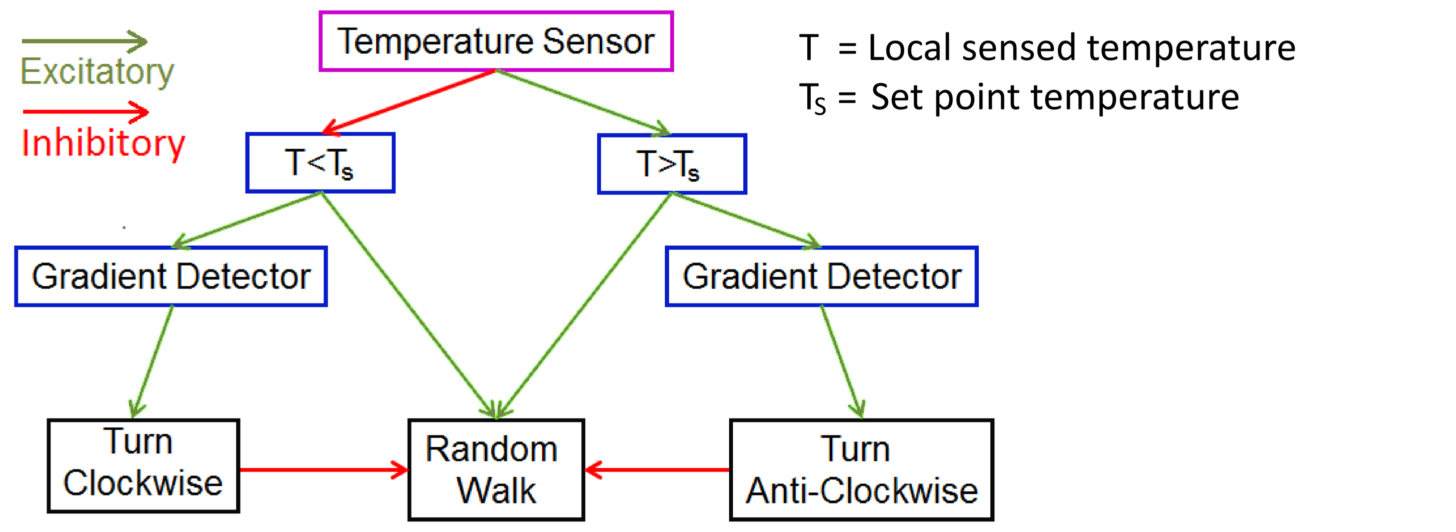
if $V\geq 0$ then $V\to V_r$ and $U(t)\to U(t)+b$

Synaptic current induced by spike at time t^f

$$I_{syn}(t) = I_s\left[\exp\left(-\frac{t-t^f}{\tau_m}\right)-\exp\left(-\frac{t-t^f}{\tau_s}\right)\right]h\left(t-t^f\right)$$

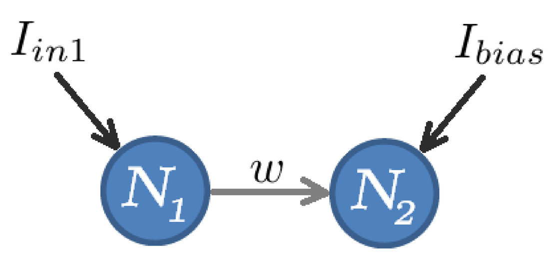
The Dynamics Model

We assume that the worm is continuously moving. The speed and direction of the worm is controlled by the neural network.



T = Local sensed temperature
T_s = Set point temperature

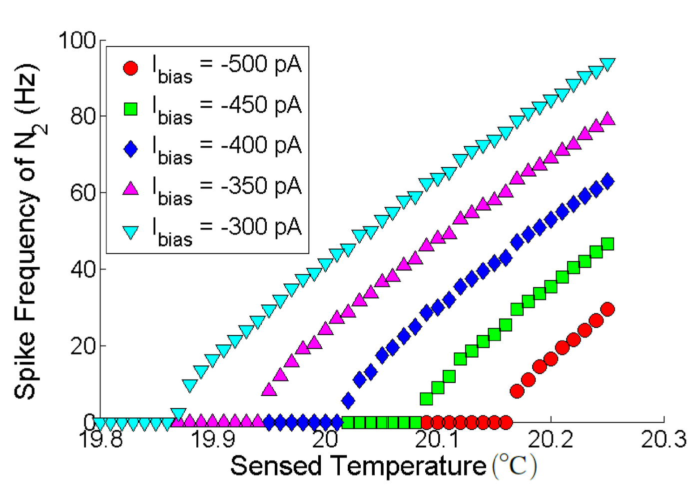
Comparator circuit

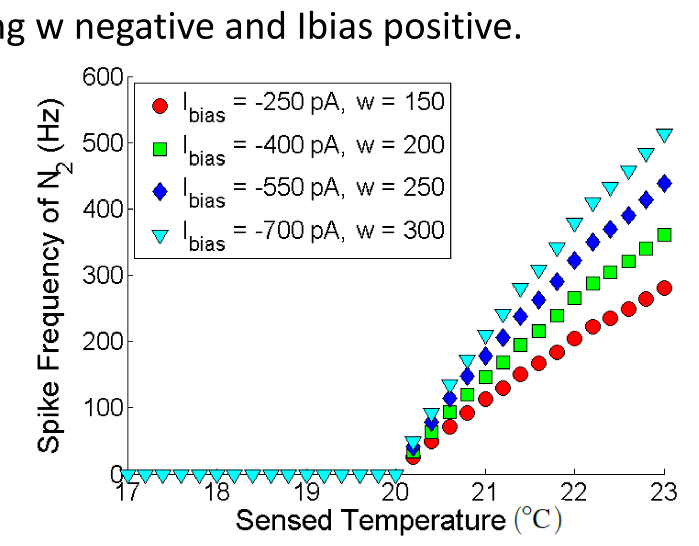


N1 is assumed to the simple linear temperature sensor with current given as:

$$I_{in1} = \alpha_T + \beta_T \times (T - T_s)$$

A complementary comparator can be realized by making w negative and Ibias positive.



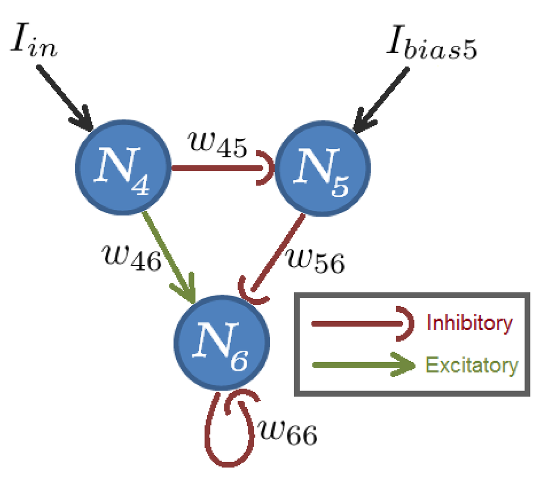


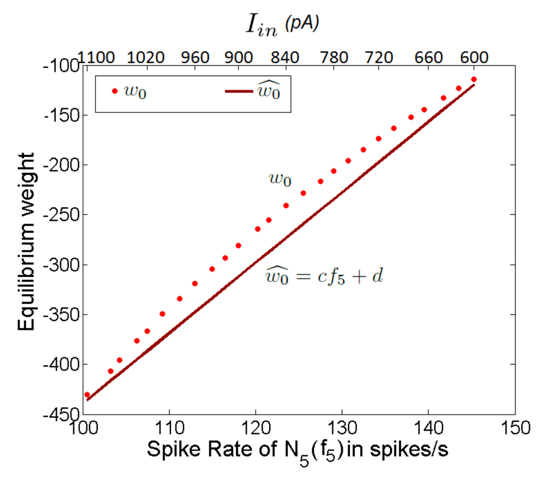
Gradient Detector

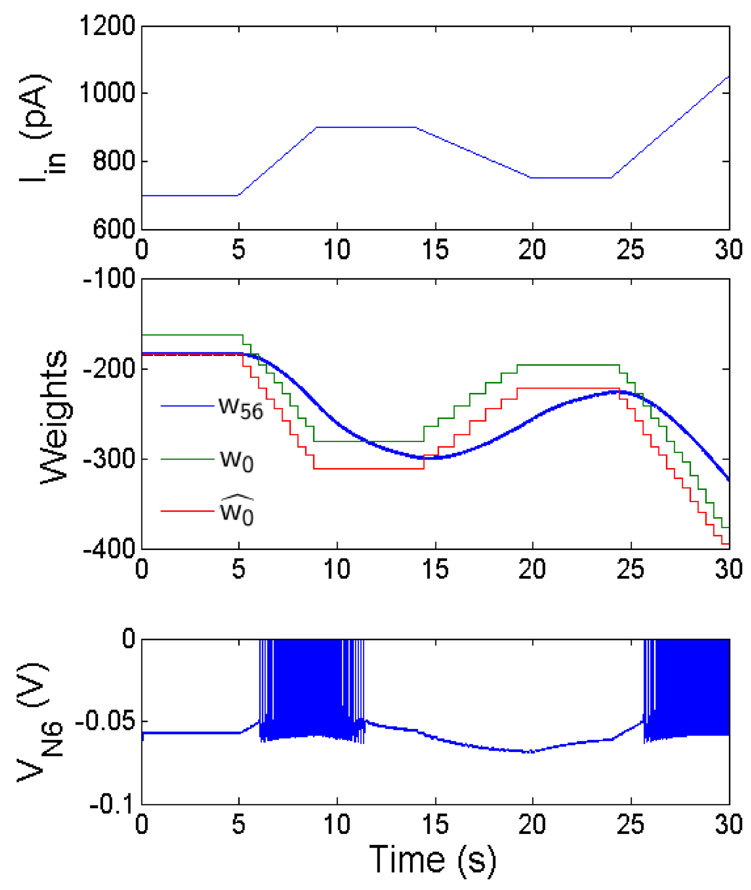
- It is an adaptive system in which w_{56} adapts to the steady state value of I_{in} to neutralize the spiking (N6 stops spiking when $|w_{56}| \geq |w_0(I_{in})|$).
- An increased current leads to spiking in N6.
- A decreased current leads to suppression of potential in N6.

$$\tau_a\frac{dw_{56}}{dt} = w_0 - w_{56}$$

- We relate w_{56} to local variable f_5 instead of I_{in} and choose a linear relationship to fit this. The fitted curve is such that $(\widehat{w_0}) < w_0$ in operating range to avoid repetitive spiking in steady state.







- We replace continuous-time equation with spike-dependent weight update rule

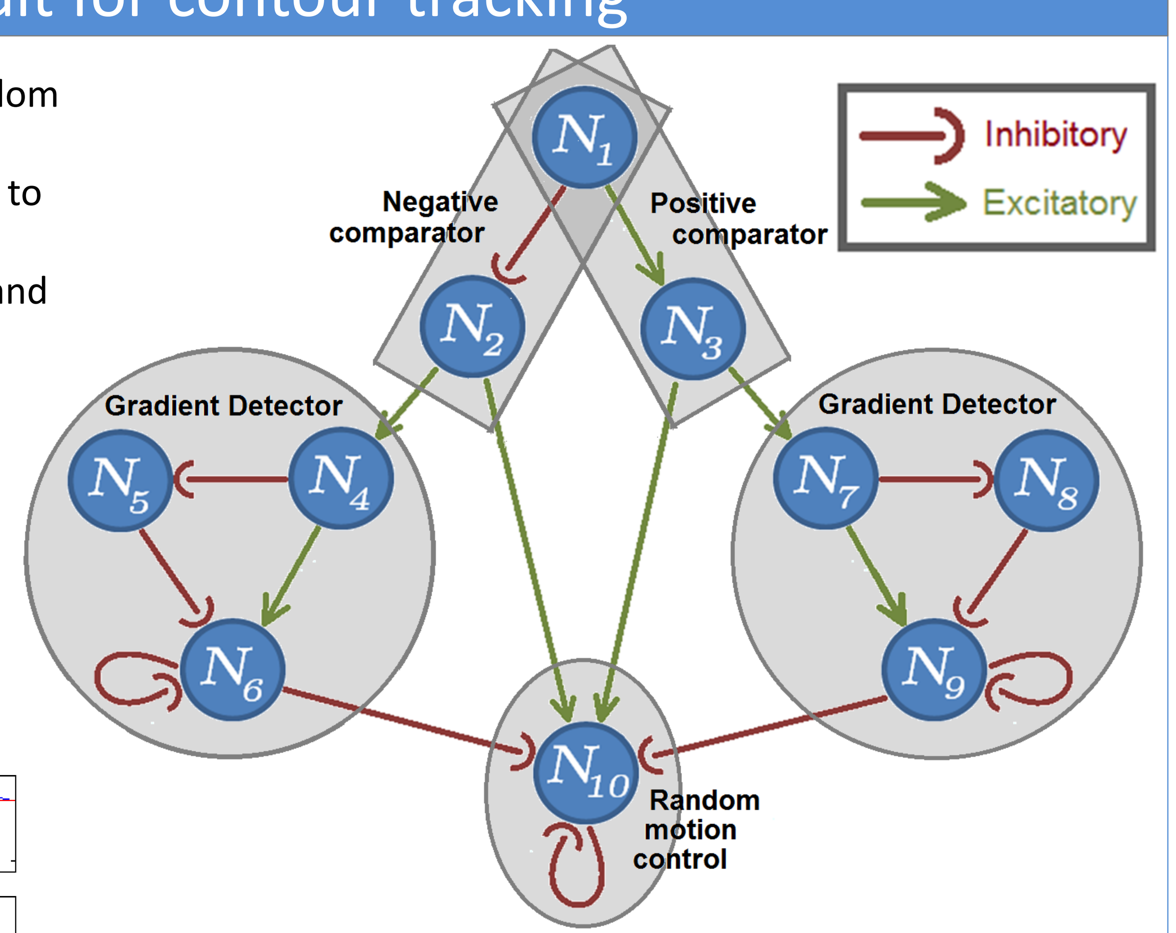
$$\Delta w_{56} = \left(\frac{c}{\tau_a}\right)f_5\Delta t + \frac{(d-w_{56})}{\tau_a}\Delta t$$

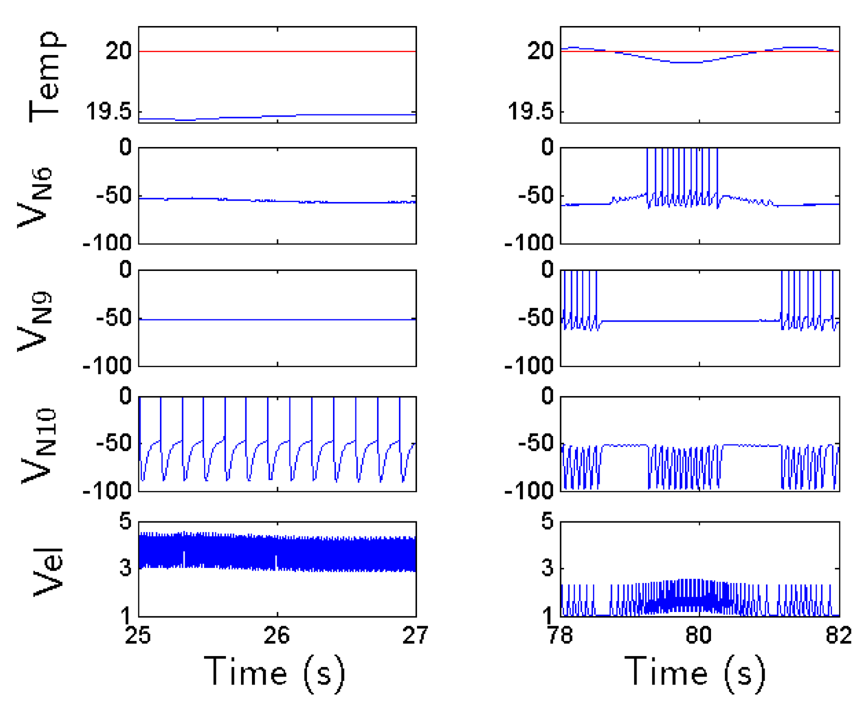
$$\Delta w_{56} = \left(\frac{c}{\tau_a}\right)\delta(t-t^{N_5}) + \frac{(d-w_{56})}{\tau_a}\Delta t$$

- τ_a affects sensitivity of GD and high values may lead to sustained spiking even after gradient has disappeared
- w_{46} controls w_0 which in turn amplifies the net current in N_6 affecting sensitivity and sustained spiking
- w_{66} is used to reduce spiking rate at high input current gradients. It can also be modelled by some sort of refractory period.

Neural circuit for contour tracking

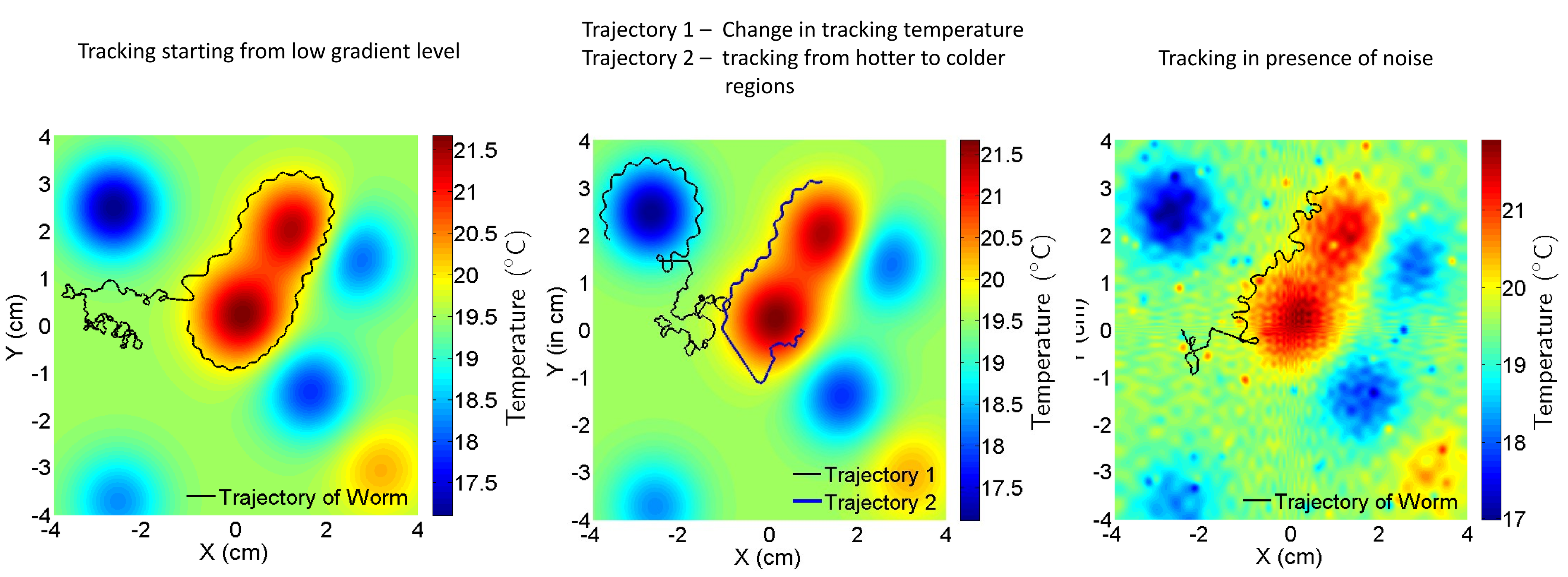
- At every spike of N10, the worm turns by a random angle uniformly distributed over -π/2 to +π/2
- The bias current into N10 alone is not sufficient to elicit any spiking. N2 and N3 inject excitatory currents into N10 when worm is not within a band around the cultivation temperature Ts.
- Worm should move faster if it is away from Ts. At every spike of either N2 or N3, the magnitude of the speed is incremented by a constant amount (1.3 mm/sec).
- In absence of any spike at either N2 or N3, the speed exponentially decays to 1 mm/sec.





- Spike patterns in the network during random exploration (left) and tracking (right).
- N6 and N9 spike in response to negative and positive temperature gradients. Their spikes actuate deterministic turns causing isothermal tracking.
- N10 spikes when they are quiet, prompting random exploration.
- When away from Ts, heavy spiking at comparator neurons causes the average speed to increase thus leading to faster exploration.

Results and performance evaluation



- For a memoryless forager, the optimal strategy to detect randomly distributed revisitable targets is to make the flight lengths between random turns follow the heavy-tailed Levy distribution. For a fair comparison with our model, we kept launch point, minimum run length and average speed for both models identical. Results were as follows:

	Metric	Levy Flight	Our model
1	Isotherm discovery success rate	39%	63%
2	Time to locate the isotherm	51.08 s ± 36.16 s	40.70 s ± 27.83 s

- This justifies the energy expended by the worm in neural computations.
- The energy consumed by this circuit depends on the number and frequency of spikes needed to make decisions. The average firing rate over the whole population of neurons is 73.89 Hz.
- The neurons spike sparsely. Local spiking frequencies rarely go above 150 Hz and never above 260 Hz, ensuring that our model is biologically plausible.

IEEE Computational Intelligence Society
2014 International Joint Conference on Neural Networks