

## BIO-INSPIRED ROBOTIC LOCOMOTION MODEL: RESPONSE TOWARDS FOOD GRADIENT CHANGES AND TEMPERATURE VARIATION

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### Abstract

The nervous system is a complex yet efficient structure - with superior information processing capabilities that surely surpass any man-made high-performance computer. Understanding this technology and utilising it in robotic navigation applications is essential to understand its underlying mechanism. One of the approaches is using a nematode's biological network model, as having a simple network structure while holding a complex locomotion behaviour. For instance, its ability to navigate via local concentration cue (chemotaxis) and the ability to dynamically respond towards surrounding temperature (thermotaxis). To date, the simulation of currently available models is on static environment conditions and the nematode's movement decision is based on the deterministic non-linear response towards gradient changes. Commonly, parameters of these models were optimised based on static conditions and require adjustment if simulated within a dynamic environment. Therefore, this work proposed a new nematode's biological locomotion model where the movement trajectory is determined by the probability of "Run" and "Turn" signals. The model is simulated within a 2D virtual environment with complex concentration gradient and variants of temperature distribution. The analysis result shows the nematode's movement of the proposed model agreed with the finding from experimental studies. Later, the proposed model in this work will be employed to develop a biological inspired multi-sensory robotic system for navigating within a dynamic and complex environment

Keywords: Bio-inspired, *C. Elegans*, Chemotaxis, Robotic navigation, Thermotaxis.

## 1. Introduction

The nervous system of *C. Elegans* is relatively simple compared to other organisms - the network consists of only 302 neurons, 6,393 chemical synapses and 890 gap junctions [1]. Notwithstanding its simplicity, the complexity of the nematode's biological behaviour is the main reason that it is used widely to study the mechanisms of the nervous system. Additionally, the invariance of its network eases the process of correlating biological behaviour with morphological structure. However, despite having full access to the connectivity map of the *C. Elegans* nervous system, the mechanisms underlying its complex behaviours remain unknown. To date, some research works were conducted to define the model of *C. Elegans* biological locomotion behaviour. Most of these works are focused on chemotaxis behaviour (biological response towards concentration gradient. The main reason chemotaxis behaviour is mainly utilised as a locomotion model is that the fundamental knowledge underlying the behaviour is well established compared to other behaviour (e.g. thermotaxis and mechanotaxis). Furthermore, accurately modelling nematode's locomotion model helps the neuroscientist understand nervous system mechanisms, which is hardly achieved in experimental works.

There are many approaches in modelling *C. Elegans* locomotion in the previous works based on chemotaxis biological behaviour. For instance, Lockery et al. proposed a chemotaxis model by defining a trained network model according to the real network connectivity of *C. Elegans*. The simulated locomotion pattern is similar to the real nematode within the controlled experimental condition. However, it only considers short-term response with the assumption that concentration gradient is fixed through time [2].

The chemotaxis model is introduced using whole network connectivity including motor neurons which integrated multiple body segments [3-6]. The network and model parameters are optimised using a dynamic neural network by feeding desired movement trajectory as training input data. The proposed locomotion behaviour model is mainly utilised in simulating biological mechanisms, helping neuroscientists understand developing networks, the functionality of specific neurons and the interaction between nodes [7-8].

On the other purpose, the *C. Elegans* behaviour model is also utilised in robotic applications, especially for defining the biological inspired robotic navigation model. For instance, the *C. Elegans* is used as a model to create a crawling robot for pothole detection [9]. Besides, Deng et al. [5, 6] provided a theoretical framework to design a snake-like locomotory model based on *C. Elegans* chemotaxis behaviour which said has the capability to find food and at the same time navigate away from a toxin area. The model assumes that pair of ASE neurons are responsible to determine a worm-like robot's new direction based on food and toxin concentration changes. Additionally, Boyle et al. developed a snake-like prototype robot controlled by a decentralized neural-based low-level motor controller, which relies on the feedback input of body posture and environment [10].

For thermotaxis behaviour, there are only a few biological models were introduced. The whole-body model of *C. Elegans* is simulated by integrating the kinematic model of muscle body and neuronal circuit that is responsible for thermotaxis behaviour [11]. Bora et al. [12] proposed a thermotaxis locomotion model using a simple network consisting of 10 spiking neurons that control direction and speed. The forward movement during area exploration is based on random

distribution. Meanwhile, the turning degree when steering towards the desired area is a deterministic value dependent on the different range of current body temperature compared to cultivation temperature,  $T_C$ ; although both of the temperature range (either larger or lower than  $T_C$ ) exhibit identical linear responses. Matsuoka et al. [13] introduced multiple responses locomotion model depend on nematode's body temperature compared to cultivation temperature, as reported in experimental works [14-17]. The turning probability distribution of nematode's model changes depend on temperature region; lower than  $T_C$ , give fix distribution while the distribution if larger than  $T_C$  depends on temperature difference relative to  $T_C$ .

In this paper, the nematode's locomotion model is proposed based on the biological movement of *C. Elegans*. The developed model was simulated in the 2D virtual environment with dynamic and complex gradient distributions. Although the model is defined using a simple artificial network and does not truly represent real biological connectivity, the model is able to navigate towards the correct direction by using locomotion strategies, as observed in experimental studies. The main contributions of this paper include three main aspects. First, the constructed locomotion model is described as a non-linear and non-deterministic model, where the decision of the locomotion trajectory depends on the probability of running and turning signal as described in [18-20].

Using a non-deterministic concept in determining the locomotion path of nematode, different trajectory paths could be generated regardless of whether the model is simulated within fixed gradient distribution. This approach enables the model to respond more natural, in which the taken path towards the desired goal not fix but influence by the ratio "Run" and "Turn" signal. Secondly, for chemotaxis behaviour, the gradient distribution in a 2D environment is designed to dynamically change during the simulation if the nematode eats a portion of the food source. This function enables the user to simulate and analyse the interaction between the nematodes.

Additionally, using the non-deterministic concept on the locomotion model, the nematode reaches its trajectory goal even though the gradient distribution changes during the simulation. Lastly, by using a similar locomotion principle, the nematode's thermotaxis behaviour was simulated. The model used different locomotion strategies depending on the local temperature range to move towards the desired condition, which agrees with the observation in the experimental studies.

The rest of this paper is structured as follows. In Section 2, the fundamental concept of *C. Elegans* chemotaxis and thermotaxis behaviour in a biological perspective based on experimental studies are discussed. Then, the simulation setup and detail of the model is explained in Section 3. In section 4, the simulation result of the nematode locomotion model in a 2D virtual environment and the detailed analysis is presented. Finally, the contributions of this paper are concluded in Section 5.

## 2. The Complexity of *C. Elegans* Biological Behaviour

### 2.1. Chemotaxis as a survival strategy: Finding a food

All organisms have a natural biological ability to find the food sources which is essential to survive in their environment. However, unlike higher and more complex organisms (e.g., humans, rats), *C. Elegans* is only equipped with a simple

mechanism that senses a concentration gradient so that it can steer towards the food source. The nematode uses two locomotion strategies in chemotaxis behaviour: “biased random walk” and “weathervane”. They are also known as *klinokenisis* and *klinotaxis*, respectively [18]. In the *klinokenisis* strategy, the network regulates the run periods and turn frequencies as a response to the concentration gradient changes. According to Luo et al. [21], chemotaxis can be classified as either positive (moving up the gradient) or negative chemotaxis (moving down the gradient). This experimental work also suggests that *C. Elegans* has the ability to remember a previous concentration gradient; in other words, a nematode cultivated at a specific concentration will move towards that concentration using either positive or negative chemotaxis. Although, the underlying circuit that differentiates the two behaviours remain unknown.

Before designing a model of biological behaviour, it is crucial to understand the physical properties responsible for that behaviour. In this case is to find the “key” neurons and their properties (how they respond to the input stimulus), along with the network connections. For example, in chemotaxis behaviour, the ASE pair of neurons (ASEL & ASER) are primarily responsible for regulating the behaviour, although other sensory neurons might also play an important role. The experiment works reported in [22, 23] clearly show that the ASE neuron pair’s response to the concentration gradient step changes and that its neural activity can be modelled using a simple sigmoid activation function. However, as reported in [23], ASEL and ASER show opposite responses to the gradient changes.

- **ASEL neuron:** If  $dC/dt > 0$ , the neural activity increases rapidly and is in ON condition. If  $dC/dt < 0 \rightarrow$  no response and in OFF condition.
- **ASER neuron:** If  $dC/dt > 0 \rightarrow$  level of internal state slightly down; assumed to be in OFF condition. If  $dC/dt < 0 \rightarrow$  neural activity increases rapidly and is in ON condition.

These studies clearly show that this neuron pair exhibits an asymmetric response to the concentration gradients and established ON-OFF relationship towards the same stimulus. Additionally, the ASER neuron is said to play an important role in experience-dependent behaviour. The experimental work done in [21] shows that ASER plays important role in negative and positive chemotaxis. Increasing the neural activity reduces the reorientation rate in negative chemotaxis and increases the reorientation rate in positive chemotaxis. This shows that ASER neuron might have another functionality - storing the memory of a previous concentration. Thus, it might be one of the reasons why the nematode can behave in either a positive or negative chemotaxis depending on the cultivation concentration.

Equally important, it was reported that other sensory neurons - ASH and ADF - show a response to the concentration gradient in which the ADF neuron functions as an ON cell and the ASH neuron as an OFF cell [23]. However, the absence of these neurons does not significantly change the chemotaxis behaviour in *C. Elegans* [23]. The critical question remains how the neural activity in sensory neurons regulates the nematode’s movement towards the preferred concentration. The answer lies in the interneuron layers that process the incoming signal and convert it into complex locomotion behaviour.

Looking at the biological connections in *C. Elegans*, three important interneurons create the next downstream layer connection to the ASE neuron pair.

They are known as the AIY, AIZ and AIB interneurons. The AIY neuron class is reported in [21] to regulate “Run” movements; its absence from the network shortens the “Run” period and increases the “Turn” rate. In contrast, the AIZ and AIB neurons regulate the “Turn” rate or have a significant role in the reorientation of the nematode position. Additionally, the study suggests that AIZ-AIY is needed in negative chemotaxis and that either AIZ-AIY or AIZ-AIB must be present for positive chemotaxis. All of these interneurons are critical for the “random walk” strategy (*klinokinesis*), but insignificant for the weathervane (*klinotaxis*).

## 2.2. Responsive to the dynamics of temperature in the environment

### 2.2.1. Complexity of thermotaxis behaviour

It is essential for cold-blood organisms like *C. Elegans* to have a special sensory-locomotion strategy to maintain body temperature. *C. Elegans* use two different strategies for thermotaxis behaviour: i) positive thermotaxis - moving up the temperature gradient to avoid cold temperatures; and ii) negative thermotaxis - escaping from a high-temperature area by moving lower on the gradient. In a normal environment, nematode has the tendency to live and display normal locomotion behaviour within the specific temperature range of  $T_c \pm 2^\circ\text{C}$  ( $T_c$  : cultivation temperature) - known as isothermal tracking. The work published by Luo et al. [14] describes experimental studies of thermotaxis behaviour in *C. Elegans*. Details on how *C. Elegans* responds to a dynamic range of temperatures are as follows:

**Positive Thermotaxis (if  $T < T_c$ ):** The nematode tends to move towards warmer temperatures; turn probability increases if the temperature gradient,  $dT/dt$ , is negative. Additionally, this behaviour only occurs in the specific condition in which temperature  $T = T_c - 5^\circ\text{C}$ , and the smallest step gradient  $dT/dt = 0.5^\circ\text{C}$  [16, 24]. As reported in [13], the analysis of nematode movement suggests that “Run” duration is approximately equal at all gradient steps. Therefore, it is assumed that the locomotory behaviour in this temperature range uses a “biased reorientation” strategy [14].

**Negative Thermotaxis (if  $T > T_c$ ):** Nematode has biased movement in colder temperatures, where reorientation probability increases if temperature change,  $dT/dt$ , is positive. Contrary to positive thermotaxis, this behaviour uses “*biased random walk*” and “*biased Orientation*” strategies [14], where the “Run” period increases if the step gradient,  $dT/dt$ , is negative - thus creating a tendency for nematode to move in the right direction towards preferred temperature.

**Isothermal Tracking (if  $T = T_c \pm 2^\circ\text{C}$ ):** *C. Elegans* favour living in a range near to  $T_c$ , known as cultivation temperature. In this temperature range, the nematode shows more “Run” and less “Turn”; the movement is more deterministic [16]. The nematode moves its head away if there are variations in temperature to stabilise the temperature alignment [16]. Thus, this behaviour can be modelled by assuming that a “slight turn” will occur if there is a temperature difference with  $T_c$ . The turning magnitude would depend on the degree of the difference.

### 2.2.2. AFD thermosensory neuron

A primary factor in thermosensory behaviour is the unique features of the AFD sensory neuron; it has the ability to i) store temperature information and ii) respond

dynamically to a range of temperatures. According to an experiment done by Kobayashi et al. [25], the AFD sensory neuron can store current body temperature,  $T_B$ , and reset the cultivation temperature,  $T_C$ . The following Eq. (1) defines this behaviour [13].

$$\frac{dT_C}{dt} = \frac{1}{\tau_{up,dwn}} (T_B - T_C) \tag{1}$$

Additionally, the neural activity of AFD varies depending on the current body temperature. The AFD neuron does not significantly response to the temperature gradients if the body's temperature is below  $T_C$ . As reported in [16], the internal state of the AFD neuron increases rapidly if  $T_B$  is near to the cultivation temperature. Tsukada et al. [15] gives the mathematical definition of a temporal neural response of the AFD neuron as shown in Eq. (2); where  $w_0$  is basal activity,  $w(t)$  is response function,  $x(t)$  is temperature input and  $\epsilon$  is noise.

$$y(t) = w_0 + \int_0^t w(t - \tau)x(\tau)dt + \epsilon \tag{2}$$

However, unlike the ASE neuron pair (chemotaxis sensor), AFD is a symmetric pair of neurons - meaning that the neural responses of AFDL and AFDR are identical. Uniquely, the output from the AFD neuron yields a bidirectional effect on the activity of the AIY interneuron [17]; it excites or/and inhibits AIY activity depending on its internal state. If there is high neural activity in AFD, it is both excitatory and inhibitory towards AIY's internal state, thus producing normal thermotaxis behaviour. A decrease in AFD activity inactivates inhibitory transmission and leaves only excitatory transmission, which boosts activity in the AIY neuron to create *thermophilic* behaviour in the nematode. In contrast, very low activity in AFD deactivates both types of transmission and makes *C. Elegans* likely to move towards colder temperatures (*cryophilic* behaviour) - an effect of high neural activity in the AIZ interneuron.

### 3. Nematode Locomotion Model

#### 3.1. Network model

This section explained in detail the network model used to simulate the biological behaviour of *C. Elegans*. Figure 1 illustrates the network model used to represent the biological behaviour of nematode.

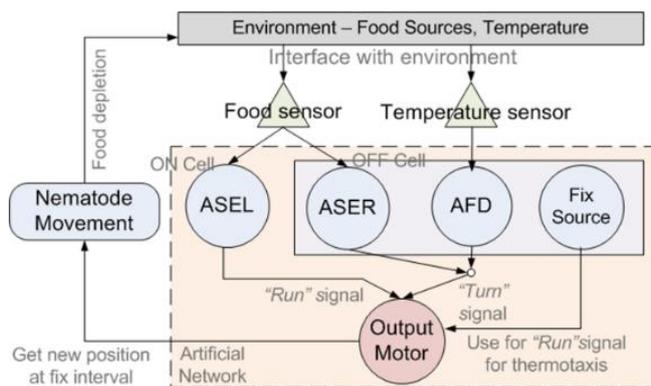


Fig. 1. Network model for chemotaxis and thermotaxis.

For simplicity, few assumptions are made:

- The nematode is modelled as a single point, not as an entire structure with different body segments. The direction of the nematode is determined by the outputs of a *motor* device.
- The AFD neuron able to store previous temperature information, although the mathematical definition used in the model is not intended to fully represent the biological mechanism.
- The “Run” signal in thermotaxis is assumed to have a fixed value; it indicates constant running probability in a real nematode.

As shown in the figure, the network interfaces with the outside environment via multiple sensory devices. For this simulation, two different sensors were created to sense the availability of food sources and temperature changes. Each of the environment sensors has a special definition and provides input to the connected sensory neuron as follows:

**Food Sensor:**

$$Input(t) = \frac{dC(t)}{dt} = C_N(t) - C_M(t) \quad (3)$$

where,

$$C_N = C(t) - C(t - k)$$

$$C_M = C(t - k) - C(t - 2k)$$

The food gradient is calculated by taking the difference in food concentration between two previous concentration windows (Eq. (3)). The *k* value is the size of the previous sample points which directly affects the sensitivity of the nematode response towards environmental changes. Therefore, setting *k* with a higher value typically decreases the response.

**Temperature Sensor:**

$$Input(t) = \frac{dT_B(t)}{dt} = T_B(t) - T_B(t - 1) \quad (4)$$

The temperature sensor is a device to collect the temperature gradient while the nematode moving to a new position. The temperature difference is defined using straight forward definition as shown in Eq. (4). Within the network, each environment sensor is connected to different sensory neuron(s). The food sensor gives input to the ASE neuron pair, while the AFD neuron responds to the input from the temperature sensor. The output from the sensory neurons represents either the “Run” signal or the “Turn” signal, affecting the movement of the nematode. The transfer function for each sensory neuron is defined as follows, designed according to the *C. Elegans* biological behaviour as described from experimental studies.

**ASEL & ASER neuron:**

$$f(x) = \begin{cases} \frac{A}{1+\exp(-k_s(x+x_0))} & (ASEL) \\ \frac{A}{1+\exp(-k_s(-x+x_0))} & (ASER) \end{cases} \quad (5)$$

where  $x = \frac{dC(t)}{dt}$

Both ASE neurons play a critical role in chemotaxis behaviour; where ASEL indicates the magnitude of “Run” probability, while the probability of nematode turning to a new direction is represented by the activity of ASER. These neurons have opposite responses to concentration changes. This ON-OFF relation can be defined using the simple sigmoid activation function shown in Eq. (5). This function relies on the food concentration changes,  $\frac{dC(t)}{dt}$ . Here, variable  $A$  represents the maximum output of the neuron,  $x_0$  is the threshold during 50% neuron activation, and  $k_s$  indicates the response sensitivity.

**AFD neuron:**

$$f(t) = T(y) + R(x) \quad (6)$$

$$R(x) = \begin{cases} \text{Max} \left( \frac{2}{\alpha + e^{-xk_r}} - 1 \right) & x \geq T_c \\ \text{Max} \left( \frac{2}{\alpha + e^{xk_r}} - 1 \right) & x < T_c \end{cases} \quad (7)$$

$$T(y) = (1 - \beta * \text{Min}) \frac{(y - T_c)^n}{k_d + (y - T_c)^n} + \text{Min} \quad (8)$$

where

$$y = T_B(t)$$

$$x = T_B(t) - T_B(t - 1)$$

$$(1 - \beta * \text{Min}) + \alpha * \text{Max} \leq 1$$

As shown in Fig. 1, output changes of the AFD neuron affect the value of the “Turn” signal. The output depends on: i) the temperature gradient, calculated using function  $R(x)$  in Eq. (7) and ii) the current temperature range, calculated using function  $T(y)$  in Eq. (8). Therefore, the turning response, at a specific simulation time,  $f(t)$  can be calculated using Eq. (6), where  $x$  is a temperature changes,  $\frac{dT_B(t)}{dt}$  while  $y$  is the current temperature  $T_B(t)$ . This information is sent to the AFD neuron at a fixed interval via a temperature sensor. Here, the constant of  $k_r$  and  $k_d$  and  $n$  determines the response sensitivity of the functions. Meanwhile, the fixed constant value of  $\alpha$  and  $\beta$  is dependent on the nematode’s body temperature range.  $\text{Min}$  and  $\text{Max}$  values are set; therefore the turn response  $f(t)$  is within the range [0:1].

### 3.2. Nematode locomotion in the environment

Using the values of the “Run” and “Turn” signals, the response of the motor device is calculated. In general, the *motor* device has two outputs:  $V_{OutL}$  and  $V_{OutR}$ . The value of these output variables fluctuates from 0 to 1 to determine the velocity and direction of the nematode. The approach used to calculate nematode movement trajectory based on the network activity is described in detail below. Firstly,  $\text{TurnProb}$  is calculated using Eq. (9) based on the “Run” and “Turn” signals; this value indicates the probability of the nematode changing the direction.

$$TurnProb = -Run + Turn + Turn_{Const} \quad (9)$$

*TurnProb* stochastically determines the value of *CoeL* and *CoeR* using the motor coefficient algorithm as described in Fig. 2. The algorithm is designed so that the nematode movement pattern is not fixed but stochastically changes depending on the turning probability. The motor coefficient values, *CoeL* and *CoeR* are then used to calculate the motor outputs,  $V_{OutL}$  and  $V_{OutR}$  by using Eq. (10) and Eq. (11), respectively.

$$V_{OutL} = \frac{1}{2}Run + Fwd_{Const} - CoeL \cdot Turn \quad (10)$$

$$V_{OutR} = \frac{1}{2}Run + Fwd_{Const} - CoeR \cdot Turn \quad (11)$$

**1. If  $\rho(TurnPob)$  return false;**

1.1 Nematode will move FORWARD; where  $CoeL(t)=1$  and  $CoeR(t)=1$

**2. Else if  $\rho(TurnProb)$  return true;**

2.1 Nematode will change direction and the  $CoeL(t)$  &  $CoeR(t)$  depend on the following conditions:

2.2 If  $CoeL(t-1)=1$   $CoeR(t-1)=1$  (previously moving FORWARD)

- If  $\rho(Bias_{Const})$  is true;  
 $CoeL(t)=0$   $CoeR(t)=1$
- If  $\rho(Bias_{Const})$  is false;  
 $CoeL(t)=1$   $CoeR(t)=0$

2.3 If  $CoeL(t-1) \neq CoeR(t-1)$  (previously TURN)

- If  $\frac{\sum_{t-n}^t TurnProb}{n} > 0.5$ ;

Maintain the same direction

$$CoeL(t)=CoeL(t-1)$$

$$CoeR(t)=CoeR(t-1)$$

- Else - Change new direction stochastically

If  $\rho(Bias_{Count})$  is true;

$$CoeL(t)=1$$
  $CoeR(t)=0$ 

If  $\rho(Bias_{Count})$  is false;

$$CoeL(t)=0$$
  $CoeR(t)=1$

**Fig. 2. Algorithm for motor coefficient.**

The values of  $V_{OutR}$  and  $V_{OutL}$  are later used to calculate velocity,  $v(t)$  and direction changes,  $d\theta(t)/dt$  by using Eq. (12) and Eq. (13), which are in turn used to determine the new nematode position. Here, the constant of  $V_{max}$  and  $\sigma_{Rate}$  is the nematode's maximum velocity and turning rate, respectively.

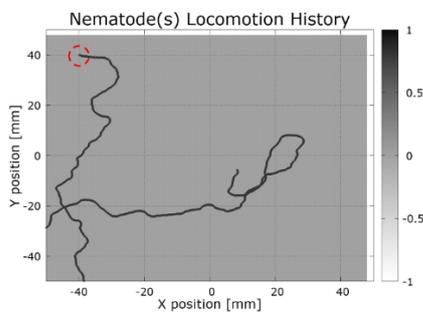
$$v(t) = V_{max} * \frac{V_{OutR}(t) + V_{OutL}(t)}{2} \quad (12)$$

$$\frac{d\theta(t)}{dt} = \sigma_{Rate} (V_{OutR}(t) - V_{OutL}(t)) \quad (13)$$

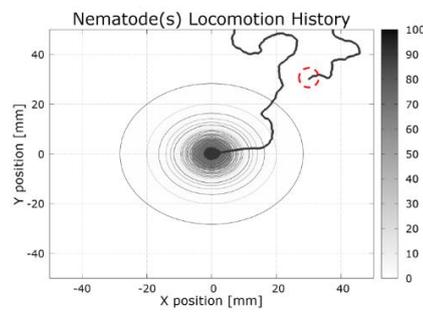
## 4. Results and Discussion

### 4.1. Chemotaxis behaviour

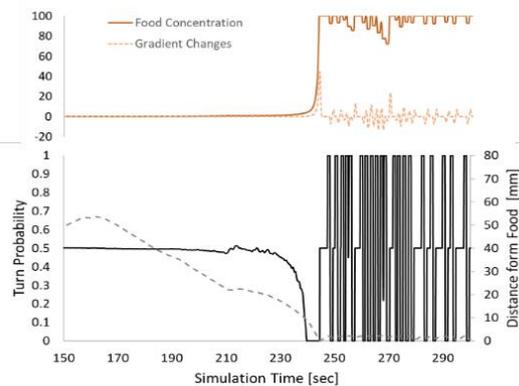
Figure 3 shows 600 sec of nematode movement within the 2D environment, where the red circle indicates the initial position. The virtual environment is set at 40mm x 40mm in size, although this is not the environment's boundary, and the nematode can move outside this area. In Fig. 3(a), the nematode was randomly moving in a non-food environment; movement was dominated by several "Run" duration with a periodic orientation change that occurred stochastically. Figure 3(b) shows the nematode's movements towards a food source according to gradient changes. Here, the nematode remained within the high-availability food area. The running duration was prolonged within the food area, and the nematode moved straight to the food source. To explain the chemotaxis behaviour of the nematode in a food-available environment, the correlation between turning probability and gradient changes was analysed. As shown in Fig. 3(c), the nematode shows constant turn probability when no gradient changes (far away from the food source). When it approaches near the food source, the turning probability sharply decreases, exhibiting a long-run moving directly towards higher concentration. The turn probability greatly fluctuated when the nematode is within a higher concentration area, keeping its position within that area.



(a) Nematode movement within the environment without a food source.



(b) Nematode movement within the environment with a food source.



(c) Relation of food concentration with the turning probability and nematode distance from food.

Fig. 3. Nematode chemotaxis behaviour simulated for 10 minutes.

### 4.2. Nematode eating behaviour

As the nematode moves within the environment, it will sense food concentration changes at a specific location and will start eating the food depending on two conditions:

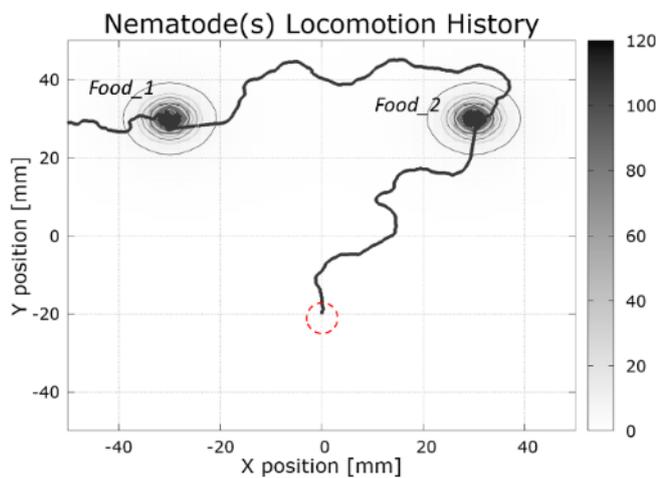
- i) **Starvation rate** - Determines the probability of the nematode eating the food at the current location.
- ii) **Food availability** - Each time the nematode decides to eat, it will consume a fixed amount of food.

Eq. (14) gives the mathematical definition of starvation rate changes, where  $\tau_{EC}$  is a time constant of nematode's energy consumption. The initial value of starvation rate is set by the user - it gives a complex simulation set up to observe the interaction between nematodes in the food environment.

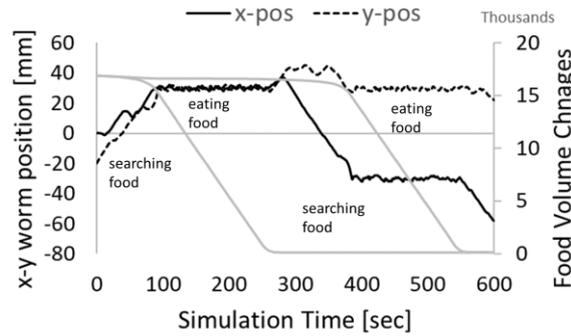
$$\frac{dStvRate(t)}{dt} = -\frac{StvRate(t)}{\tau_{EC}} \tag{14}$$

$$Fod\ Volume = \begin{cases} \pi r_0^2 H + \frac{2}{2-n} \pi r_0^n H (max_b^{2-n} - r_0^{2-n}) & n < 2 \\ \pi r_0^2 H + 2\pi r_0^2 \log\left(\frac{max_b}{r_0}\right) H & n = 2 \\ \pi r_0^2 H + \frac{2}{n-2} \pi r_0^2 H \left(1 - \left(\frac{r_0}{max}\right)^{n-2}\right) & n > 2 \end{cases} \tag{15}$$

The total volume of each food source in the virtual environment is calculated using Eq. (15). This equation is derived from simple volume integration and depend on the value is depending on the decay value. However, as the distribution is an exponential function, the maximum food distribution area needs to be limit at  $r = 1000$ , so the approximate volume can be calculated.



(a) Nematode movement.

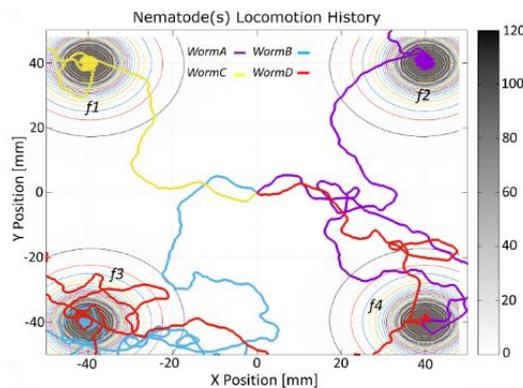


(b) Food volume changes and nematode x-y spatial position.  
**Fig. 4. Nematode eating behaviour**

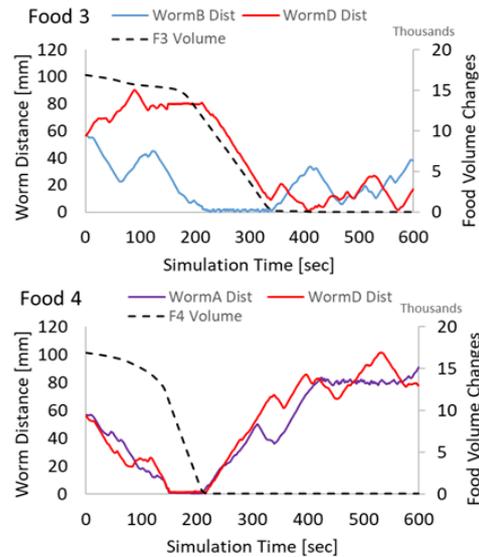
**4.3. Interaction of multiple nematodes within the same environment**

The simulator is capable of handling multiple nematodes within the same environment. Figure 5 shows an example of the behaviour of four nematodes simulated for 10 minutes which were initially placed at the same starting point within the environment. Each nematode is set with a similar initial velocity, starvation rate and network parameters. However, the initial direction angle is assigned randomly for each nematode. During the simulation, each nematode is navigated to find the food sources and competed with other nematodes for the available food sources.

As shown in Fig. 5(a), all the nematodes initially move randomly before moving towards food sources by sensing the gradient changes. The path decision of each nematode greatly relies on surrounding food concentration which dynamically changes. For instance, *WormB* and *WormD* went almost simultaneously to the same food source (*f4*). As shown in the figures, the trajectory movement of both nematodes towards *f4* was significantly affected. When the *f4* was depleted, *WormD* went to the next nearest available food source (*f3*). Although the *WormD* was able to navigate towards the food source correctly, it did not stay within the area for a long time as that food already depleted. The nematode starts moving randomly to begin searching for a new food source.



(a) Nematodes movement for 10 minutes simulation.



(b) Distance of nematodes from the food source and food volume depletion.

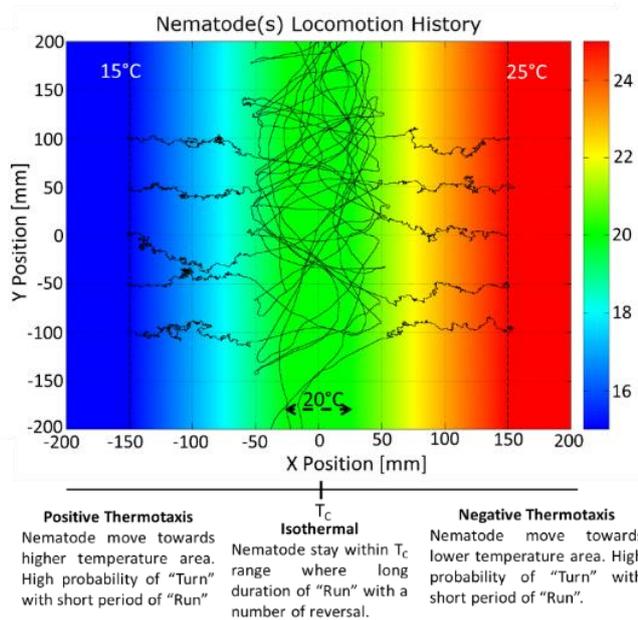
Fig. 5. Interaction of multiple nematodes within the same environment.

#### 4.4. Thermotaxis behaviour

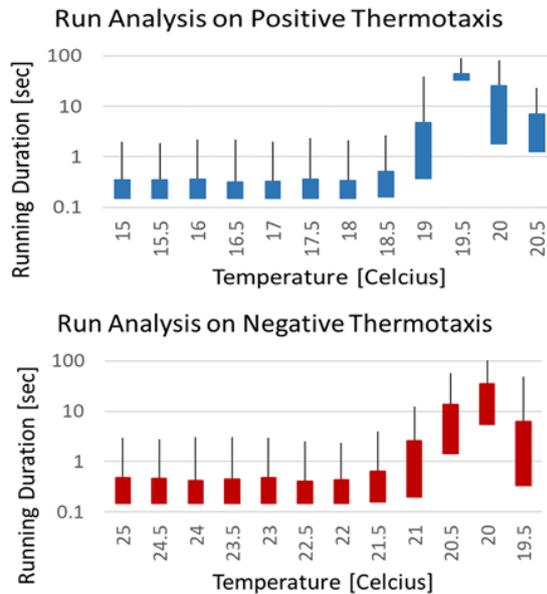
Figure 6 shows the nematode response towards temperature changes in the 2D environment. In Fig. 6(a), the environment has been set up to have a linear temperature gradient. The linear temperature gradient ranges between 15 to 25 degrees on the x-axis. Ten nematodes were divided into two groups within the environment, and each group is placed at 15 °C and 25 °C, respectively. The cultivation temperature,  $T_C$  of each nematode is set at 20 °C. As shown in the figure, the nematodes used different strategies to navigate towards the cultivated temperature area. The nematodes placed at the colder areas shows positive thermotaxis behaviour with a short duration of “Run” and approximately constant turning probability. Meanwhile, the nematodes from the warmer area used the negative thermotaxis strategy to navigate towards  $T_C$ . The turning probability and running duration vary slightly depend on the temperature area and gradient changes. On average, the nematode from the warmer area arrived within  $T_C$  area approximately 1.7 times earlier than the group from the colder area. Within the  $T_C$  area, the nematode shows isothermal behaviour with a long-run period and a small number of sharp reversals to preserve its locality within the cultivated temperature.

The model was also tested in variant temperature distribution with different linear-gradient steepness, as shown in Fig. 7(a). Here, three nematodes are initially placed at 25, 18 and 15 degrees. The simulation runs for 60 minutes and  $T_C = 20^\circ\text{C}$ . At the end of the simulation, *worm\_A* and *worm\_B* both were able to find their way to the cultivated temperature area. However, as shown in Fig. 7(b), when the nematode has encountered the area without gradient changes, the turning probability is constant, making the nematodes keep changing their orientation with a high number of sharp reversals. For instance, *worm\_B* and *worm\_C* - at 25 degrees and 18 degrees, respectively (see Fig. 7(b)). Additionally, the nematode when steering towards the

desired temperature shows a longer period of running with a short interval of turn and numbers of sharp reversals which occurred within 2-3 seconds when encountering negative gradient (e.g *worm\_A* at 16.5°C -17.5°C area). The nematode, however, when arrived at  $T_C$  area, shows a long period of run with an interval of orientation correction if encounters temperature out from  $T_C$  range.

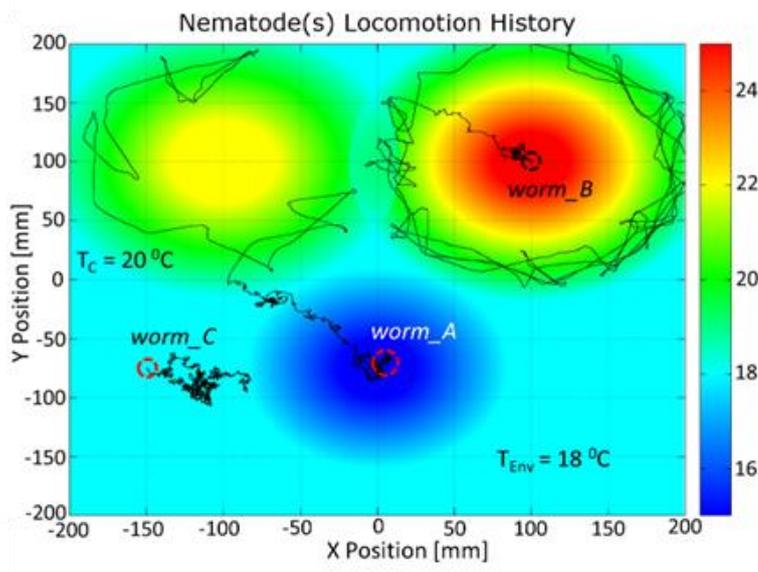


(a) Nematodes movement within linear temperature gradient.

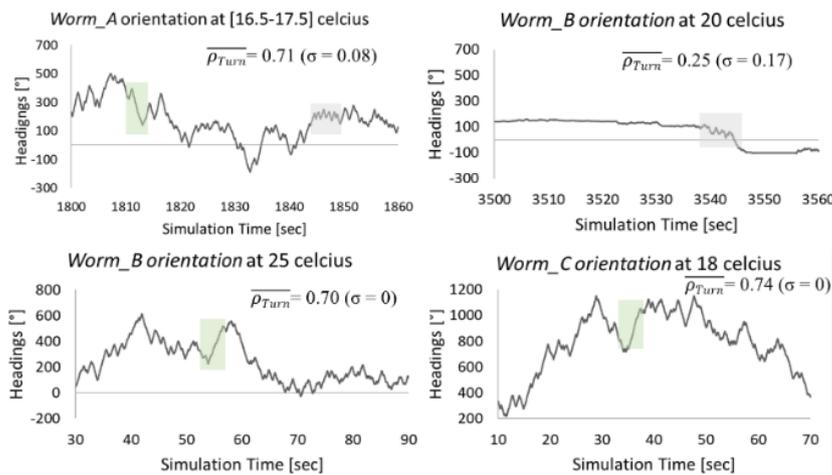


(b) Average running duration of each temperature.

**Fig. 6. Thermotaxis behaviour using an artificial network.**



**(a) Nematodes movement within different temperature distributions and gradient steepness.**



**(b) Orientation changes of nematodes at different temperature ranges.**

**Fig. 7. Thermotaxis behaviour using an artificial network.**

From these two important nematode’s locomotion behaviours, it is clearly showing that the proposed locomotion model in this paper is able to demonstrate the biological movement pattern of biological *C. Elegans*. However, the current model only consists of two simple layers - sensory input and motor output. The nematode movement, however in reality occurs because of the contraction and relaxation of muscle cells, which depend directly on the activity of motor neurons. Therefore, in future work, simulation using full connectivity of the biological

network model is essential to explain the behaviour of each neuron and the interaction between them. Nevertheless, it is worth mentioning that there is still a limitation on our knowledge of nematode's network properties, such as synaptic weight or propagation delay. In common practice, these properties are randomly defined before finely tunes using optimisation techniques, such as genetic evolution algorithms. Nevertheless, by having a locomotion model with complete network connectivity, it also can be utilised for understanding the development of the nervous system in *C. Elegans* as proposed by Kamarudin et al. [26]. Moreover, the nematode is a creature living in a complex environment and can make the best decision for its survival depend on the environment ques as discussed in [27]. Therefore, developing a nematode locomotion model capable of responding to multiple stimulus input is essential to enhance the current model. For instance, finding food within dynamic temperature variants.

## 5. Conclusions

In this paper, a new locomotion model of *C. Elegans* according to biological perspective was proposed. The model was tested with two different behaviour: chemotaxis and thermotaxis. In chemotaxis behaviour, the nematode model moves towards high food concentration area by sensing the local concentration gradient. The model was also designed, so the nematode will eat the food which dynamically changes surrounding concentration. Besides, simulating multiple nematodes within the same virtual environment, the interaction between nematodes can be studied by analysing their trajectory pattern according to the environment changes. Furthermore, using the same locomotion model, the nematode's thermotaxis behaviour was simulated by replacing sensory neurons that respond to temperature variant distribution. As a result, the nematode model is able to navigate using different locomotion strategies depending on the temperature range with respect to the cultivation temperature. The future work for this study will focus on the simulation using full biological connectivity of nematode with different stimulus integration within the same simulation environment, which later can apply for the biological inspired robotic navigation system.

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### Nomenclatures

$C_M$	Concentration gradient changes from $k-2k$ previous sample
$C_N$	Concentration gradient changes from $k$ previous sample
$CoeL$	The motor device left output's coefficient
$CoeR$	The motor device right output's coefficient
$H$	Food height at peak concentration
$k$	Size of sample in food sensor device
$k_d$	Control sensitivity in AFD neuron's temperature response
$k_r$	Control sensitivity in AFD neuron's turn response
$k_s$	Response sensitivity of ASE pair neuron

$r_o$	Radius of food at peak concentration
$T_B$	Nematode's body temperature
$T_C$	Nematode's cultivation temperature
$w_0$	Basal activity in AFD neuron
$x_o$	Threshold level at 50% of ASE activation function
<b>Greek Symbols</b>	
$\alpha$	Constant in temperature gradient response function $R(x)$
$\beta$	Constant in temperature range response function $T(y)$
$\varepsilon$	Noise in AFD temporal neural response
$\theta$	Use to shows angle changes $d\theta/dt$
$\rho$	Probability of turning
$\sigma$	Nematode turning rate
$\tau$	Time constant related in thermotaxis behaviour

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