Encoding sensory information in spiking neural network for the control of autonomous agents

Nicolas Oros, Rod Adams, Neil Davey, Lola Cañamero, Volker Steuber
Biocomputation and neural network group
University of Hertfordshire
AL10 9AB
United Kingdom
{N.Oros, V.Steuber, R.G.Adams, N.Davey, L.Canamero}@herts.ac.uk

Abstract

The goal of the work presented here was to find a model of a spiking sensory neuron that could cope with small variations of a simulated pheromone concentration and also the whole range of concentrations. We tried many different functions to map the pheromone concentration into the current of the sensory neuron in order to produce a near linear relationship between the concentration and the firing rate of the sensor. After unsuccessful trials using linear currents, we created an equation that would by definition achieve this task and used it as a model to help us find a similar function that is also used in biology. We concluded that by using a biologically plausible sigmoid function in our model to map pheromone concentration to current, we could produce agents able to detect the whole range of pheromone concentration as well as small variations. Now, the sensory neurons used in our model are able to encode the stimulus intensity into appropriate firing rates.

1 Introduction

In this project, we want to have agents able to find pheromones in the environment. Initially, the pheromones are diffused in a circle where the concentration is the highest at the centre and is linearly decreasing, down to the borders of the circle (Fig. 1). Subsequently, they may be produced and diffused by other agents that may move in the environment but they will still have a differential value with distance. In order to create these agents, we need to decide which kind of sensory neurons we want to use. One challenge of using a spiking neural network is to decide the coding to use in order to map information received by a sensor that will transform these stimuli into spikes.

Different approaches can be used (Fig. 2) [Floreano, D. and Mattiussi, C., 2001]:

a) Mapping stimulus intensity to the firing rate of the neuron
b) Mapping stimulus intensity onto the number of neurons firing at the same time
c) Mapping stimulus intensity onto the firing delay of the neuron

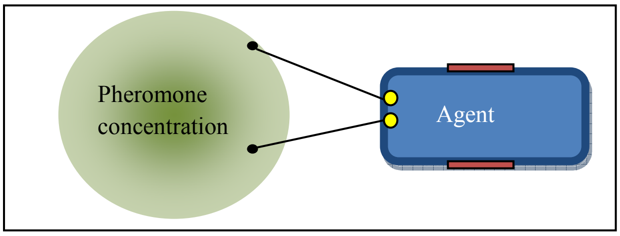

Figure 1. An agent equipped with two wheels (red) and two antennae (black) linked to two sensory neurons (yellow) used to detect pheromones.

In order to use one of these encoding schemes, one needs first to decide how the input current of a sensor should represent its stimulus intensity. Therefore, the current received by a sensor will be different from the one received by a neuron because it will be based on the external stimulus intensity and not the activity of other neurons or sensors. We want an agent to be able to detect small variation of pheromone concentration but also the whole range of concentrations. Therefore, the agents must be equipped with sensory neurons that can produce spike trains at different frequencies depending on the pheromone concentration. The ideal case would be to have a linear relationship between the pheromone concentration and the firing rate of the sensory neuron. Such relationship exists in biological systems. For example in Humans, the relationship between increases in frequency of firing and pressure on the skin is linear [Kandell, E. R. and Schwartz, J. H. and Jessel, T. M., 2000]. Therefore, we tried to find out if such a relationship was possible by carrying out different experiments using different definitions for the sensory neuron's current.

2 Experiments

We implemented, in a JAVA program, one sensory neuron that was a leaky integrate-and-fire neuron and tried different equations to calculate its unique input current. The sensor current was always calculated depending on the pheromone concentration: I = f(C). If the membrane potential which depends on the current I, reaches a certain threshold θ, the sensory neuron emits a spike. Therefore, the firing rate of the sensory neuron depends on the shape of the current. In our experiments, we tried many different equations to calculate the current having linear and non-linear relationship with the pheromone concentration in order to have a quasi-linear relationship between the pheromone concentration and the firing rate of the sensory neuron.

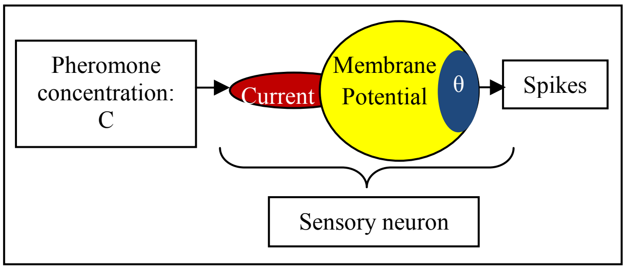

Figure 3. Mapping pheromone concentration into spikes

We first set the sensor's input to be a concentration of 1 and we recorded at what time a spike was emitted in order to determine the frequency (firing rate). We apply the same method to study the firing rate of the sensors over the whole range of pheromone concentration (1 to 300). We didn't want the sensory neuron to fire if the concentration was equal to 0 so only the presence of pheromones could stimulate a sensor. Afterwards, we implemented each different kind of sensory neuron implementing the different equations into an agent and looked at its behaviour.

2.1. Linear relationship between current and pheromone concentration

We first carried out a few experiments implementing a simple linear relationship between the sensory information *S* (pheromones concentration in our case) and the current *I* [Fig. 4] and studied the sensor's firing rate recorded as frequency in all the subsequent figures.

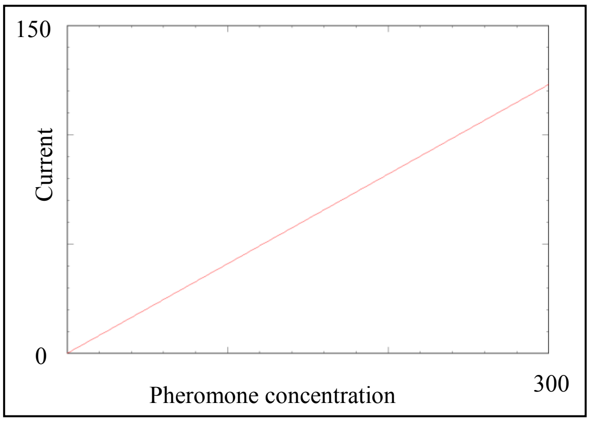

Fig 4. Current input to sensory neuron

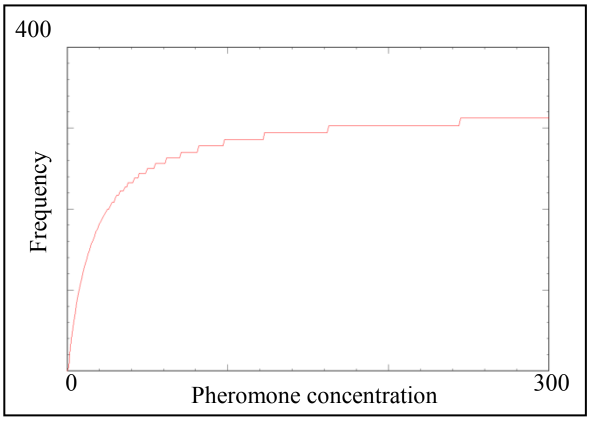

Fig 5. Resultant firing rate of sensory neuron

After a few experiments using different values for *K*, we realized that the sensor was saturating [Fig. 5] due to the nature of the sensory neuron (leaky integrate-and-fire [Koch, C., 1999]). In fact, above a small value of pheromone concentration, the current produced was too high and the sensor fired at its maximum rate. After implementation in the agent, we saw that it was not able to detect the difference between a concentration of 200 and 250 for example.

2.2. Linear relationship between current and pheromone concentration with offset

Then, we tried to use the same equation but with an added baseline current and a much smaller slope (K2) [Fig 6]. We made these changes knowing that our sensor responds to a small range of currents with a large bandwidth.

(2) $I = K_1 + K_2 S$ With $K_1 = 0.41$ and $K_2 = 0.0053$

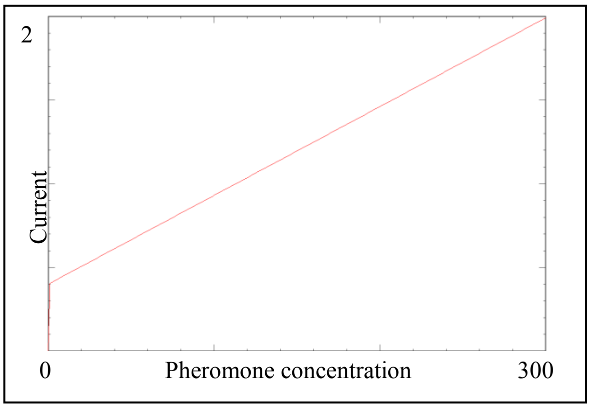

Fig 6. Current input to sensory neuron

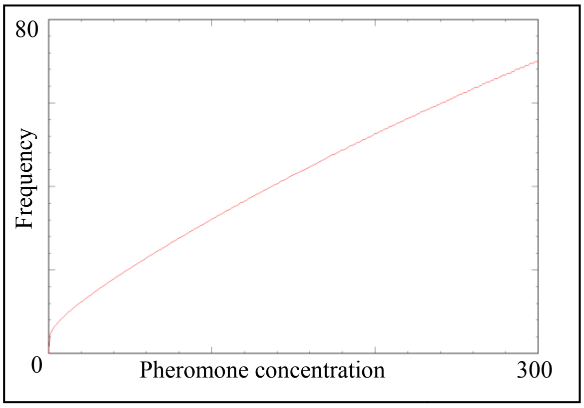

Fig 7. Resultant firing rate of sensory neuron

With this equation, we had a more linear relationship between the pheromone concentration and the firing rate of the sensor [Fig 7] so the agent should have been able to detect smaller variations. Unfortunately, the sensor did not use its whole bandwidth so it could not cope with very small values of the concentration. Therefore, another kind of equation had to be tried.

2.3. Non-linear relationship between current and pheromone concentration

Concerning the neurons we are using, we know the limits of currents and the corresponding firing rate. For every cell (motoneurons, sensors, and interneurons):
$I_{min} \approx 0.4$ (f = 0.61 Hz)
$I_{saturation} \approx 20$ (f = 300 Hz)

We also know that the firing rate of a leaky integrate-and-fire neuron is given by [Koch, C., 1999]:

$$(3)\ \langle f \rangle = \frac{1}{T_{th} + t_{ref}} = \frac{1}{t_{ref} - \tau \ln\left(1 - {V_{th}}/{I.R}\right)}$$

Where:

- T_{th} is the time of a spike emission.
- V_{th} is the threshold voltage (a spike is emitted if the membrane potential is above this value).
- T_{ref} is the refractory period.
- I is the current
- R is a resistance (constant)
- τ = R.C (time constant)
- C is a capacitance (constant)

Given that our sensory neuron is modelled as a leaky integrate-and-fire neuron, we inverted the previous equation to find an equation for the current [Fig 8] that would always produce a linear relationship between the pheromone concentration and the firing rate of the sensory neuron [Fig 9]. We created this equation (4) to indicate the sort of function needed for the current rather than attempting to find a correct function by guessing.

$$(4)\ I = \frac{V_{th}}{R}\left[\frac{1}{1 - \exp\left(\frac{t_{ref}}{\tau} - \frac{1}{S.\tau}\right)}\right]$$

With:

$\langle f \rangle$ replaced by S

$$\frac{V_{th}}{R} = 0.4$$

$$t_{ref} = 3/1000 = 0.003$$

$$\tau = 1/20 = 0.05$$

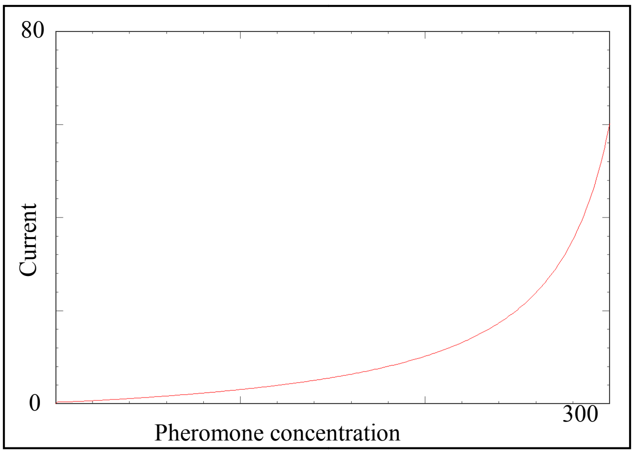

Fig 8. Current input to sensory neuron

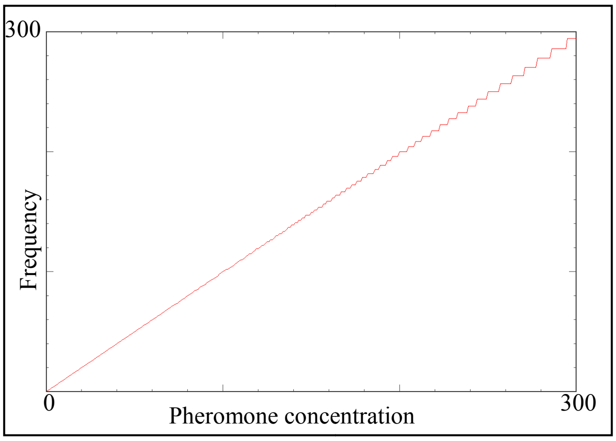

Fig 9. Resultant firing rate of sensory neuron

With this equation, an agent is able to detect a small variation in the pheromones concentration using its whole bandwidth. But we created this equation artificially so we decided to look for a similar equation commonly found in biological systems.

2.4. Hill functions

We know that molecules present in pheromones and other odours bind to proteins situated in an animal's olfactory sensory neurons [Wyatt, T.D., 2003]. And the current generated by the sensory neurons depends on their binding capacity. We first investigated an equation used by biochemists describing the binding of ligand molecules to proteins: Hill functions [Stryer, L., 1988].

$$(5)\quad h(x,k,m) = \frac{x^m}{k^m + x^m}$$

Where:

- k is the concentration of molecules when h is equal to 0.5
- *m* is the Hill coefficient and is considered as an estimate of the number of binding sites of a protein.
- x is the concentration of ligands

Archibald Hill used this equation in 1910 to describe the binding of oxygen to Hemoglobin (sigmoidal curve). It seems appropriate to use Hill functions to describe the shape of the current produced by the sensor as they are very similar to (4).

1) The first Hill function we used was too simple to be able to fit with the function (4). Once again, we realized that the sensor was saturating quite rapidly [Fig 10 and 11].

$$(6)\quad I = K_1 \times \left(\frac{S}{K_2 + S} \right)$$ With $K_1 = 50$ and $K_2 = 100$

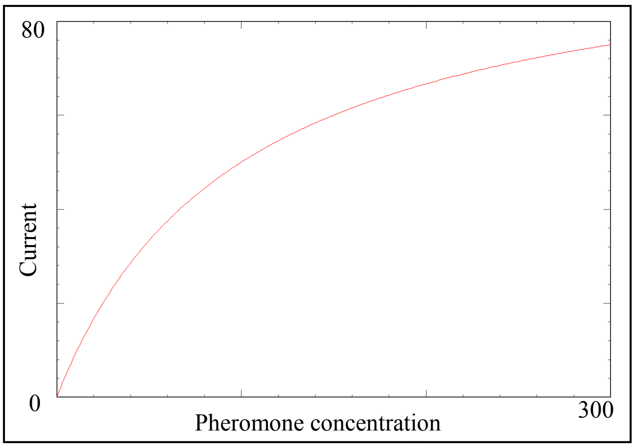

Fig 10. Current input to sensory neuron

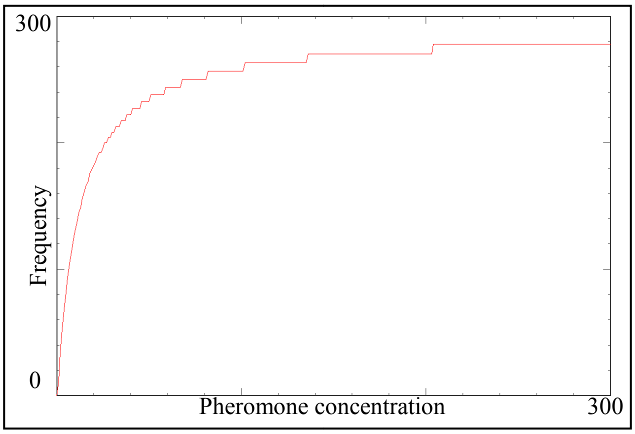

Fig 11. Resultant firing rate of sensory neuron

2) The second Hill function we used was:

$$(7)\qquad I = K_1 \times \frac{S^m}{K_2^m + S^m}$$

With $K_1 = 2.38*10^{\wedge 7}$, $K_2 = 7104$ and $m = 4.13$

We used Matlab to find correct constant values in order to minimize the difference between the two functions (7, red curve) and (4, dashed curve in blue) in order to have a function that could create a linear relationship between the pheromone concentration and the firing rate of a sensory neuron like the function (4) [Fig 12].

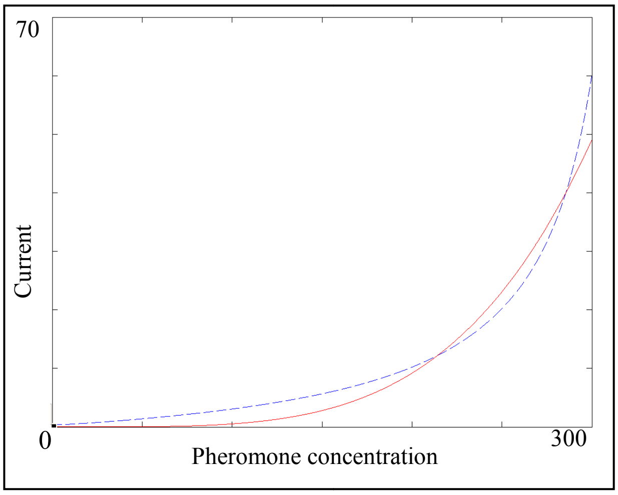

Fig 12. Current input to sensory neuron

Unfortunately, this function was not as good as (4). In fact, the sensor could not detect a pheromone concentration of 1. So we decided to add an offset to the function.

2.5. Hill functions with offset

$$(8)\ I = K_1 \times \frac{S^m}{K_2^m + S^m} + b$$

[Fig 11] With $K_1 = 2.33*10^{\wedge 6}$, $K_2 = 2348$, $m = 5.23$ and $b = 2.65$
[Fig 12] With $K_1 = 3.45*10^{\wedge 4}$, $K_2 = 1378$, $m = 4.297$ and $b = 0.4$

This time, Matlab found a value for b too high so the sensor could fire even if it did not perceive any pheromones [Fig 13]. So we tried to constrain the value of b to be less than 0.4 [Fig 14]. Unfortunately, the current produced was the same (= 0.4) for a large range of small pheromone concentration so the agent could not detect differences of concentration in this range. We concluded that it was difficult to use a Hill function for the sensors' current so that the agents would be able to detect a very small and very high pheromone concentration. Hill functions are sigmoidal so we decided to use a more general sigmoid function.

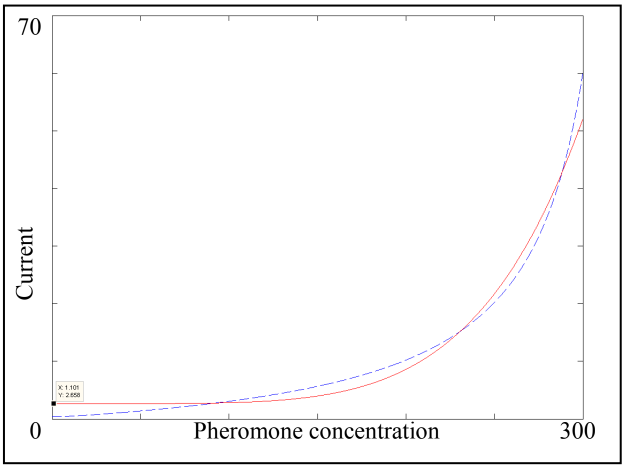

Fig 13. Current input to sensory neuron

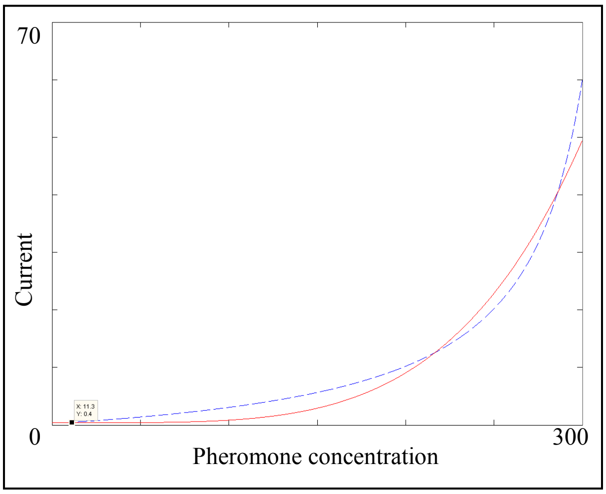

Fig 14. Current input to sensory neuron (b = 0.4)

2.6. Sigmoid function

$$(9)\ I = K_1 \times \frac{1}{1 + \exp\left(\frac{h - S}{K_2}\right)}$$

With $K_1 = 2.38*10^{\wedge 8}$, $K_2 = 59.35$ and $h = 1210$

We also used Matlab to fit this function to (4) [Fig 15]. Unfortunately, the sensor could not detect 1 unit of pheromone so we added an offset to the function.

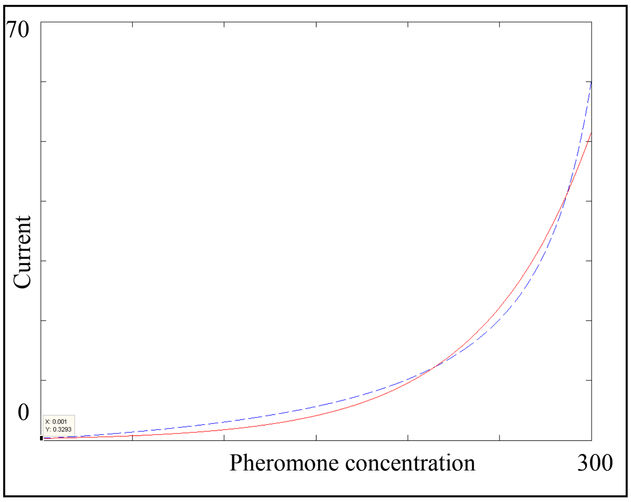

Fig 15. Current input to sensory neuron

2.7. Sigmoid function with offset

300

$$(10)\ I = K_1 \times \frac{1}{1 + \exp\left(\frac{h - S}{K_2}\right)} + b$$

[Fig 14] With $K_1 = 2.7*10^{\wedge 7}$, $K_2 = 51$, $h = 973$ and $b = 1.7$
[Fig 15] With $K_1 = 3.9*10^{\wedge 4}$, $K_2 = 59$, $h = 691$ and $b = 0.08$

Matlab found a function very similar to (4) but with an offset too high [Fig 16]. So the sensor was firing even when it did not receive any information. This is why we constrained b to be less than 0.08. Matlab found a very similar function with a small offset [Fig 17]. After implementing this function into a sensor, we produced a relationship between the pheromone concentration and the sensor's firing rate [Fig 18] that was less linear than by using (4) but perfectly adequate to allow the agent to detect small and large variation of pheromones.

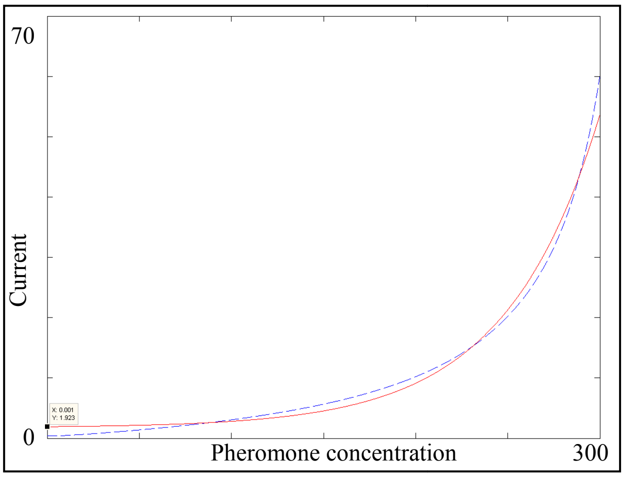

Fig 16. Current input to sensory neuron

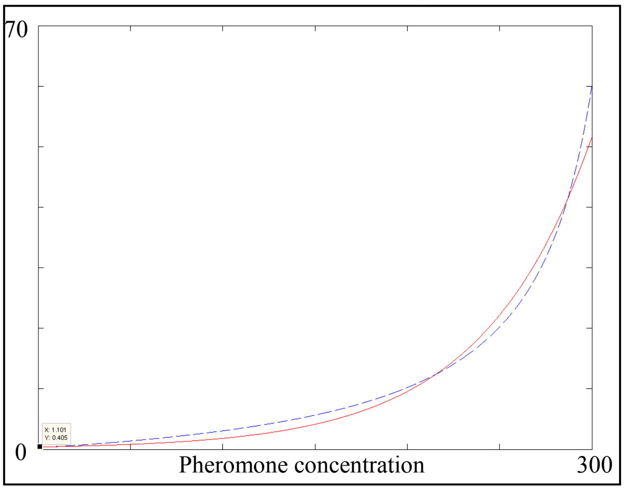

Fig 17. Current input to sensory neuron (b = 0.08)

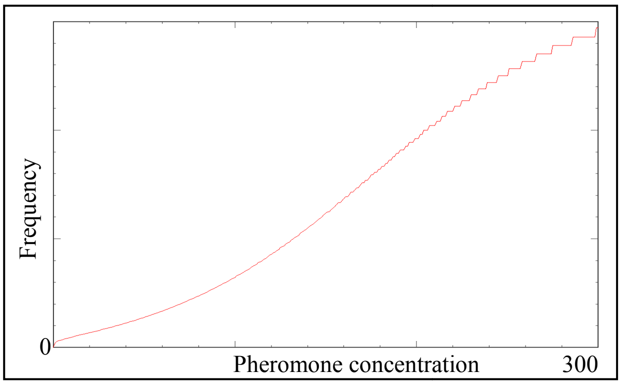

Fig 18. Resultant firing rate of sensory neuron

3 Conclusion

Our goal is to create agents able to find pheromones that are diffused in a circle where the concentration is the highest at the centre and is decreasing down to the borders of the circle. In order to achieve this goal, we had to find a model of spiking sensory neuron that could cope with small variations of the pheromone concentration and also the whole range of concentrations. We tried many different functions to map the pheromone concentration into the current of the sensory neuron in order to produce of linear relationship between the concentration and the firing rate of the sensor. After unsuccessful trials using linear currents, we created an equation that would by definition achieve this task and used it as a model to help us find a similar function that is also used in biology. We concluded that by using a biologically plausible sigmoid function in our model to map pheromone concentration to current, we could produce agents able to detect the whole range of pheromone concentration as well as small variations. Now, the sensory neurons used in our model are able to encode the stimulus intensity into appropriate firing rates.

References

[Floreano, D. and Mattiussi, C., 2001], Evolution of Spiking Neural Controllers for Autonomous Vision-Based Robots. In *Proceedings of the international Symposium on Evolutionary Robotics From intelligent Robotics To Artificial Life* (October 18 - 19, 2001). T. Gomi, Ed. Lecture Notes In Computer Science, vol. 2217. Springer-Verlag, London, 38-61.

[Kandell, E. R. and Schwartz, J. H. and Jessel, T. M., 2000], "Principles of Neural Science", 4th edition, McGraw-Hill.

[Koch, C., 1999], Biophysics of computation, Information processing in single neurons, Oxford University Press: New York, New York.

[Stryer, L., 1988], *Biochemistry*, Third Edition, W. H. Freeman and Company, New York.

[Wyatt, T.D., 2003], *Pheromones and Animal Behaviour, Communication by Smell and Taste*, Cambridge University Press.