

Modeling a Honeybee using Spiking Neural Network to Simulate Nectar Reporting Behavior

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ABSTRACT

Swarm cognition is the field that explores the possibility of implanting human cognitive functions on machines by transplanting the processes in naturally self-organized colonies. These natural colonies, especially ant colony, honey bee colony, etc, have been deeply studied to explore the factors which enable them to simulate high cognitive functions, such as decision making, labor division, etc. In swarm cognition a human neuron is matched to an ant or a honeybee in a colony, because both have limited capabilities and their reactions mainly depend only on local interactions with their neighbors. This paper has postulated that any individual in a swarm is itself a network of neurons and thereby swarm is a network of networks. Each child network react to its neighboring networks such a way that where the mother network will be enabled to respond appropriately to the environmental changes. Accordingly, the paper models a honeybee as a network of neurons. The basic model is evaluated by simulating the behavior that a honeybee generates when it reports the food sources to the colony members. A neuron was modeled as a spiking neuron and the network consists of excitatory and inhibitory spiking neurons. The results have demonstrated that the proposed model is capable of demonstrating food reporting process of a honeybee.

General Terms

Artificial Intelligence, Swarm Cognition

Keywords

Swarm Cognition, Spiking Neurons, Honeybee Foraging

1. INTRODUCTION

In the field of Swarm Cognition[1] the cooperative behavior of the large number of unsophisticated agents has been studied. Though these unsophisticated agents have very limited capabilities but with their cooperative and local interactions they have demonstrated globally interesting behaviors that is necessary for their survival. Their interactions can be direct or indirect. Visual or audio contact, such as waggle dance and tremble dance, of honeybees are examples of direct communication while stigmergy or pheromones based communication between social insects are some examples for indirect communication[2].

It has been identified that self-organization as the key parameter that allows these colonies to demonstrate high level cognitive functions such as food foraging, division of labor, nest-selection, etc. By analyzing these cognitive behaviors of natural self-organized systems many efficient algorithms have been developed to solve and to optimize the complex problems mainly in human society. These swarm-based algorithms are capable of providing low cost, efficient, and robust solutions to solve complex problems in other information societies. Ant Colony Optimization (ACO)[3],

Artificial Bee Colony (ABC)[4], and Particle Swarm Optimization(PSO) are such significant swarm algorithms which have been developed by observing the ants food foraging, honeybee food foraging and nest selection, and birds flocking behaviors respectively. The principle of these algorithms are successfully applied in image and data analysis, machine learning, operational research, and in finance and business applications[5]. Moreover many significant attempts[6,7] have been made in developing models to demonstrate the dynamicity of these societies, and to investigate how random fluctuations of the key parameters of self-organization affect to the decision making process of the swarm.

These cooperative interactions of a swarm have been further analyzed in terms of understanding higher cognitive behaviors of human beings[8]. Swarm cognition works on the basic postulation that a neuron as a part of the brain can be expressed in similar to a social insect as a part of a colony. A neuron in isolation has very limited capabilities and depends only on local interactions[9], however, brain demonstrates highly complex cognitive processes similar to what swarm displays as a colony. Artificial neural network[10] is considered as a key technique to model both short-term and long-term memory on machines. Undisputedly, the cognition that arises in colonies should then be able to demonstrate by the neurons in neural network as a local and cooperative interactions of those artificial neurons. Although a bee is an unsophisticated agent with limited capabilities, it can sense fragrance of flower patches, quantity of foods available, etc. After all it has the ability to remember those findings for a short period of time and conveys these facts to the colony. This indicates that a bee itself is a network of neurons which has capability to self-organize its activity to generate appropriate outputs.

As in swarm cognition, this paper postulates that a self-organized colony is similar to a self-organized neural network where individual entity in the network is also a self-organized network that generates local outputs which allow the mother network to generate appropriate global outputs to the environment. Under this conjecture, the paper presents a model which explains a honeybee as local interactions of excited and, inhibited spiking neurons. The proposed model has been especially designed to simulate local interactions and cooperation occurred within a honeybee in particular when it communicates the food sources to the colony.

2. NECTAR FORAGING OF HONEYBEES

A honeybee foraging process and communication patterns were analyzed to identify the key parameters that are used to communicate information about the found food sources to their community. Usually honeybees communicate through various communication channels such as using pheromones,

or tactile dancing with or without some vibrating sounds. Among many communication channels, waggle dance has been used by honeybees to inform new rewarding flowering sites to the colony and to recruit new foragers to the newly found flower patches[11]. The process of waggle dance with all its key features in general ecology of nectar foraging of honeybees can be described as follows:

A colony is composed of a queen, female workers and drones. These worker bees are mainly responsible of caring hives, such as cleaning the hive, caring the larvae and youngs, feeding the queen and the drones, making honey, and gathering and storing nectar, water, etc. Therefore, the larger portion of the colony is workers and small of portion of them are scouts who search flower patches[12]. A scout keeps searching until its energy level is depleted or it finds flower-patches. If it finds a flower patch, it comes to the comb and unloads the nectar sources to the receivers at the comb. The receiver takes the nectar to the storage area of the hive. The returned scout can either be a scout again, or a forager, or an unemployed bee. If the returned scout feels that the flower patch from where it brought the nectar is in high quality and quantity, it performs waggle dance to recruit more foragers. If it is in considerable quality it simply returns and brings the nectar from the flower patch. Otherwise, a scout can forget the visited flower patch and settle as an unemployed bee until it is recruited. Or it can become a scout again searching for new flower patches.

Sometimes forager bees perform tremble dances to get unemployed bees to engage in nectar-receiving task [13, 14]. Key message that a forager wants to convey through this tremble dance is that it has found more-rewarding nectar source and no enough receivers to unload them efficiently. Meanwhile by performing this dance the forager tries to inform other mate-foragers not to recruit additional foragers to their nectar sources. Therefore, the tremble dances of a honeybee helps the colony to keep the balance between nectar storing and nectar take-in. Once foragers unload their nectar they may start to perform waggle dance to recruit unemployed foragers to visit their explored flower patches. If a forager bee has to wait too long to unload the nectar (when it was unable to find a receiver), then the forager bee does not perform the waggle dance to recruit additional foragers bees, because it does not have enough receivers to handle the unloading process. The receiver bee may get delayed for searching further away through the hive when the hive has not enough vacant storage cells, and it is almost full.

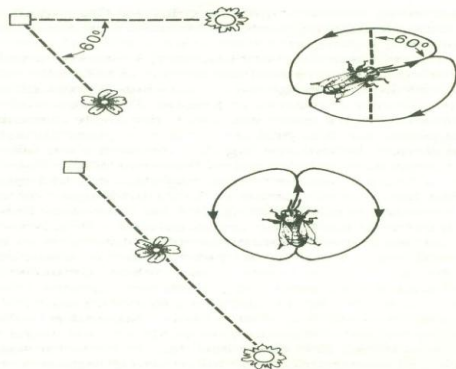


Fig 1: Waggle dance of a honeybee

Waggle dance [7,11,15-17] is a communication behavior which conveys the information about locations, and quality

(high concentration, distance, easy to collect, etc) of the food sources that have been found. A dancing bee runs forward and performs the waggle dance as shown in the figure 1, while she is on the run, she vibrates her abdomen laterally and then comes back to her starting point. According to the sources in the literature, a distance to the food source is proportioned to the length of this waggle run and the angle of the run to the sun represents the direction of the food sources. The higher the quality of nectar source, the higher the number of waggle runs per dancing bout and that increases the number of recruiters. Furthermore, the number of recruiters increases in proportion to the probability of returning forger would dance and the number of waggle runs made by her per visit. Through this mechanism the colony gathers nectar more efficiently by sending foragers to the better flower patches by abandoning less reward flower-patches, recruiting to more-rewarding patches, and searching for new patches.

According to Seeley[16], a honeybee measures the profitability of located nectar source by sensing the energetic efficiency of its foraging. Therefore, the number of waggle runs per dance is not directly a linear function of closeness of the located nectar source to the hive but the energy expenditure per foraging trip. Moreover, through its waggle dance, a dancing bee reports on the current level of energy profitability of her forage site. Therefore, the number of waggle runs per bout is high when the nectar source is abundant, and it is low when it is scarce. The dancing bee does not perform her dance in one place but distributes it over the dance floor. Therefore when number of forage sites are being reported on the dancing floor, foragers can easily take a random sample of the dance information. This allows the colony to allocate foragers to more-rewarding food sources.

3. BIOLOGY OF A HONEYBEE

Nervous system of a honeybee (*Apis mellifera*) comprises of the brain which is situated in the head, ocellus on the top of the brain, sub-esophageal ganglion which is at the bottom of the brain and seven other ganglia which are situated in the thorax and the abdomen. (two in the thorax and five in the abdomen) [18].

Nerve fibers connect the brain in to the ganglia, which resembles the spinal cord in higher animals. Ganglia seems to be work independently in their most of the functions, however they can be controlled by the brain also. Ganglia send the various information as well as feedbacks from internal and external environment to the main brain. So their behavior is a function of combine action of their brain and the ganglia. With this arrangement adult honeybee is capable to produce a range of complex behavior and execute some cognitive functions such as learning and short-term memory [19].

The brain of an adult is proportionately larger in comparison with its size. In the worker bee brain consists of the optic lobe that coordinate the visual sensations mainly. The central part (complex) of the brain seems acting as the main coordinating center [20]. So we hypothesized a simple neuronal model involving optic lobes central complex sub-esophageal ganglion and the thoracic and abdominal ganglia to explain the bee foraging behavior by assigning representative neurons for each component.

In our hypothesized model the visual stimulus which are coming through the optic lobes (distance, direction to the sun, and other visual inputs) sub-esophageal ganglion (quantity and quality of the nectar) is relayed in the inter neurons of central complex it holds them in the short term memory, see figure 2. Once the scout bee returns back to the colony it will

execute its dance mainly through the thoracic and optic ganglia depending on the feedback generated from the central complex. The rest of the colony through their mirror systems

perceives this dance behavior (mainly through the central complex) and then selection flower patch will be done accordingly.

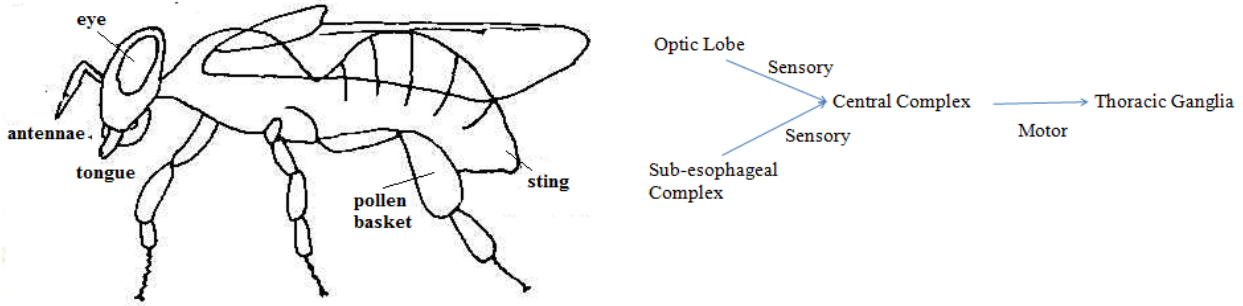


Fig. 2: Schema to illustrate neural networks involved with honeybee foraging behavior

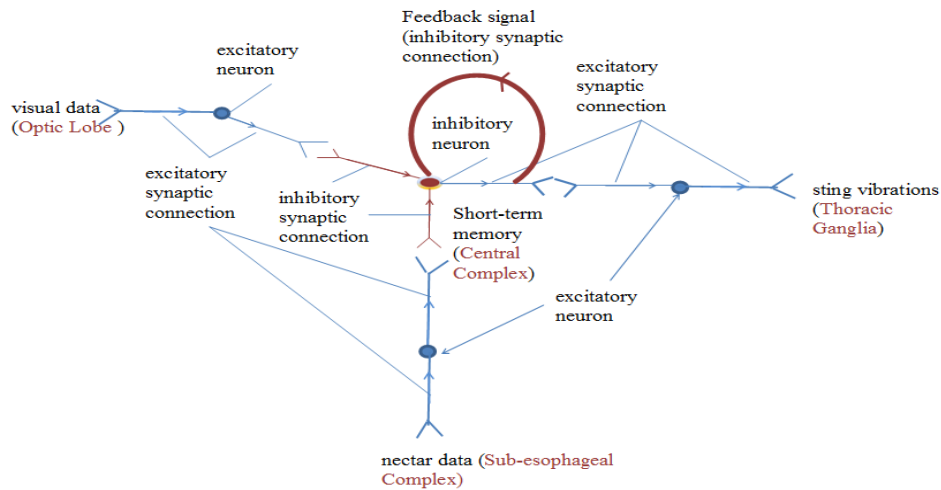


Fig. 3: The skeleton of the neural network in terms of excitatory and inhibitory neurons

In order to test this hypothesis we assigned two neurons (sensory) for the visual and sub-esophageal ganglia and one interneuron for the central complex. One motor neuron was assigned for the thoracic and abdominal ganglia conveying signals to execute the dance. Feedback loops also assigned from each destination from and to the central complex. The figure.3 depicts the skeleton of the neural network structure used to model a honeybee foraging behavior. Each neuron is connected to other neurons through a single synaptic connection.

4. MODELING SPIKING NEURAL NETWORK

A simplified spiking neuronal model of Izhikevich [21] was used to model neurons in our neural network. The simplified model is a derivative of Hodgkin-Huxley biophysical model and has high computational efficiency similar to integrate-and-fire neuron model. This model describes dynamics of neurons using set of ordinal differential equations, eq.(1-3) as described in below:

$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I \quad (1)$$

$$\frac{du}{dt} = a(bv - u) \quad (2)$$

with the auxiliary after-spike resetting

$$\text{if } v \geq 30\text{mv, then } v \leftarrow c, u \leftarrow u + d \quad (3)$$

where v is the membrane potential of a neuron, u is the membrane recovery variable which controls both K^+ and Na^+ ionic currents. The external current or the injected current is $I(pA)$. The parameters a , b , and c describe the time scale of u , sensitivity of the u to v , and after spike reset value for v respectively. The parameter t (ms) is the time step.

Izhikevich [27] has estimated these parameters and many complicated cortical neuronal dynamics have been simulated using them. According to the findings, when v reaches to 30mv , a spike is generated, and both v and u are reset as in eq.(3).

For excitatory neurons: a is 0.02, b is 0.2, c is -65mv , and d is 8. The inhibitory neurons or inter-neurons in the cortical cells are in two classes: fast spiking neurons and low-threshold spiking neurons. For our model we use low-threshold spiking neuron model because it is capable of retaining short-term

memory. For the inhibitory neurons, the values for the parameters are $a = 0.02$, $b = 0.25$, $c = -65$ *mv* and $d = 2$.

The ordinal differential equations in (1-2) can be further extended as in eq.(4-5) to describe the membrane potential updates of neurons due to synaptic conductance.

$$I_{syn} = \sum_j w_j^{in} g_j^{in}(t) (E_j^{in} - v(t)) \quad (4)$$

$$g_j^{in} \leftarrow g_j^{in} + 1 \quad \text{if spike is generated}$$

$$g_j^{in} = g_j^{in} / \tau_g \quad (5)$$

where I_{syn} is the total synaptic current received by a neuron, w_j^{in} is the weight of the j^{th} pre-synaptic connection, g_j^{in} is the total ionic conductance of j^{th} pre-synaptic connection, E_j^{in} is the reverse potential of j^{th} pre-synaptic neuron, and $\tau_g = 10ms$ is the time decay constant for ionic conductance. We set $w_j^{in} = 0.07$ for excitatory synapses and $w_j^{in} = 0.18$ for inhibitory synapses. Furthermore, reverse potential for excitatory neurons are set to $E_j^{in} = -30mv$ and reverse potential for inhibitory neurons are set to $E_j^{in} = -85mv$. The eq.(1) can be updated as in eq.(6) to integrate the pre-synaptic current, I_{syn} .

$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I + I_{syn} \quad (6)$$

The findings of Izhikevich [27] about human cortical neurons were adjusted to simulate the neuronal dynamics of honeybees. As per the findings of [22, 23], a spike is generated by a neuron of a honeybee when membrane potential of a honeybee's neuron reaches to $+45mv$. Therefore, the eq.(3) is adjusted to release a spike at $+45mv$. We assumed that values of all the other parameters remain the same for the honeybee's neurons.

5. IMPLEMENTATION AND RESULTS

The relevant Matlab code for the network in figure.3 is given in figure.4. The modeled spiking neural network of a honeybee was evaluated under following six criteria to examine the output generated by the network .

- Criteria 1: quantity of the nectar source is low, and quality of the nectar source is low.
- Criteria 2: quantity of the nectar source is low, and quality of the nectar source is high.
- Criteria 3: quantity of the nectar source is high, and quality of the nectar source is low.
- Criteria 4: quantity of the nectar source is high, and quality of the nectar source is high.
- Criteria 5: quantity of the nectar source is very high, and quality of the nectar is very high, for a shorter period of time.
- Criteria 6: quantity of the nectar source is very high, and quality of the nectar is very high, for a longer period of time.

Quantity of the nectar that honeybee has foraged is fed to the function by the parameter $plapp_1$ and corresponding quality of the nectar has been feed to the system by using the parameter $plapp_2$. The parameters $startTime$ and $endTime$ specify the starting time and the ending time of the honeybee dance. From figure.5 to figure.10 illustrate the outputs generated under each criterion. Each figure from figure.5 to figure.10 has four subplots which shows the output (change of membrane potential in *mv*) generated by each neuron.

```
function
SimulationHoneyBee(pIapp_1,pIapp_2,startTime,
endTime)
total_legnth_time = 2000;
n = 4;
dt = 0.5;

T = ceil(total_legnth_time/dt);
neuroPara = ones(4,n);
v = zeros(T,n);
u = zeros(T,n);
v(1,:) = -70
u(1,:) = -14;

neuroPara(1,:) = 0.02;
neuroPara(2,:) = 0.2; neuroPara(2,3) = 0.25;
neuroPara(3,:) = -65;
neuroPara(4,:) = 8; neuroPara(4,3) = 2;
in_synapse_hidden = 3;
g_in_hidden = zeros(in_synapse_hidden,1);
E_in_hidden = zeros(in_synapse_hidden,1);
E_in_hidden(:,1) = -85;
w_in_hidden = 0.9 * 2 * ones(1,in_synapse_hidden);
tau_g_hidden = 10;
p_inter = 0;
in_synapse_motor = 1; g_in_motor =
zeros(in_synapse_motor,1);
E_in_motor = zeros(in_synapse_motor,1);
E_in_motor(in_synapse_motor,1) = -30;
w_in_motor = 0.07 * ones(1, in_synapse_motor);
tau_g_motor = 10;

for t = 1:T-1

if t*dt > startTime && t*dt < endTime
    Iapp1 = pIapp_1;
    Iapp2 = pIapp_2;
else
    Iapp1 = 0;
    Iapp2 = 0;
end
if v(t,1) < 45
    dv = (0.04* v(t,1)+5)*v(t,1)+140-u(t,1);
    v(t+1,1) = v(t,1) + (dv +Iapp1)*dt;
    du = neuroPara(1,1)* (neuroPara(2,1)*v(t,1) -
u(t,1));
    u(t+1,1) = u(t,1) + dt*du;
    p_visual = 0;
else
    p_visual = 1;
    v(t,1) = 45;
    v(t+1,1) = neuroPara(3,1);
    u(t+1,1) = u(t,1)+ neuroPara(4,1);
```

```

end
if v(t,2)< 45
    dv = (0.04* v(t,2)+5)*v(t,2)+140-u(t,2);
    v(t+1,2)= v(t,2)+ (dv +iapp2)*dt;
    du = neuroPara(1,2)* (neuroPara(2,2)*v(t,2) -
u(t,2));
    u(t+1,2) = u(t,2) + dt*du;
    p_quality = 0;
else
    p_quality = 1;
    v(t,2) = 45;
    v(t+1,2) = neuroPara(3,2);
    u(t+1,2) = u(t,2)+ neuroPara(4,2);
end
g_in_hidden(1,1) = g_in_hidden(1,1) + p_visual;
g_in_hidden(2,1) = g_in_hidden(2,1) + p_quality;
g_in_hidden(3,1) = g_in_hidden(3,1) + p_inter;
iapp_hidden = w_in_hidden * (g_in_hidden .*
E_in_hidden);
iapp_hidden = iapp_hidden - (w_in_hidden *
g_in_hidden).* v(t,3);
g_in_hidden = (1- dt/tau_g_hidden)*g_in_hidden;
if v(t,3)< 45
    dv = (0.04* v(t,3)+5)*v(t,3)+140-u(t,3);
    v(t+1,3)= v(t,3)+ (dv + iapp_hidden)*dt;
    du = neuroPara(1,3)* (neuroPara(2,3)*v(t,3) -
u(t,3));
    u(t+1,3) = u(t,3) + dt*du;
    p_inter = 0;
else
    v(t,3) = 45;
    v(t+1,3) = neuroPara(3,3);
    u(t+1,3) = u(t,3) + neuroPara(4,3);
    p_inter = 1;
end

g_in_motor(1,1) = g_in_motor(1,1) + p_inter;
iapp_motor = w_in_motor * (g_in_motor .*
E_in_motor);
iapp_motor = iapp_motor - (w_in_motor *
g_in_motor).* v(t,4);
g_in_motor = (1- dt/tau_g_motor)*g_in_motor;

```

```

if v(t,4)< 45
    dv = (0.04* v(t,4)+5)*v(t,4)+140-u(t,4);
    v(t+1,4)= v(t,4)+ (dv + iapp_motor)*dt;
    du = neuroPara(1,4)* (neuroPara(2,4)*v(t,4) -
u(t,4));
    u(t+1,4) = u(t,4) + dt*du;
    p_motor = 0;
else
    v(t,4) = 45;
    v(t+1,4) = neuroPara(3,4);
    u(t+1,4) = u(t,4) + neuroPara(4,4);
    p_motor = 1;
end

plot((0:T-1)*dt,v(:,1),'r');
title('Excited Neuron that simulates Nectar
Quantity');
xlabel('Time[ms]');
ylabel('Membrant voltage [mV]');
figure
plot((0:T-1)*dt,v(:,2),'b');
title('Excited Neuron that simulates Nectar
Quality');
xlabel('Time[ms]');
ylabel('Membrant voltage [mV]');
figure
plot((0:T-1)*dt,v(:,3),'m');
title('Interneuron Neuron that simulates Short-term
Memory');
xlabel('Time[ms]');
ylabel('Membrant voltage [mV]');
figure
plot((0:T-1)*dt,v(:,4),'k');
title('Excited Neuron that simulates Sting
Vibrations');
xlabel('Time[ms]');
ylabel('Membrant voltage [mV]');

end

```

Fig.4: The corresponding Matlab code of the modeled spiking -neural network.

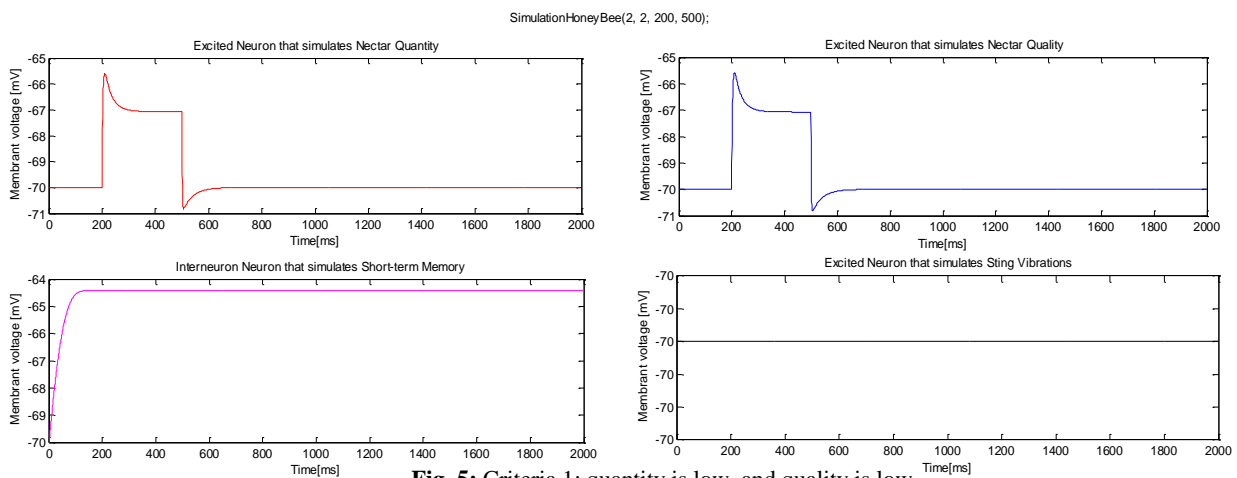


Fig. 5: Criteria 1: quantity is low, and quality is low.

Matlab function " *SimulationHoneyBee* " is called with parameters where quantity of food sources were fed as 2, quality of food source was fed as 2, for the period of 300 ms.

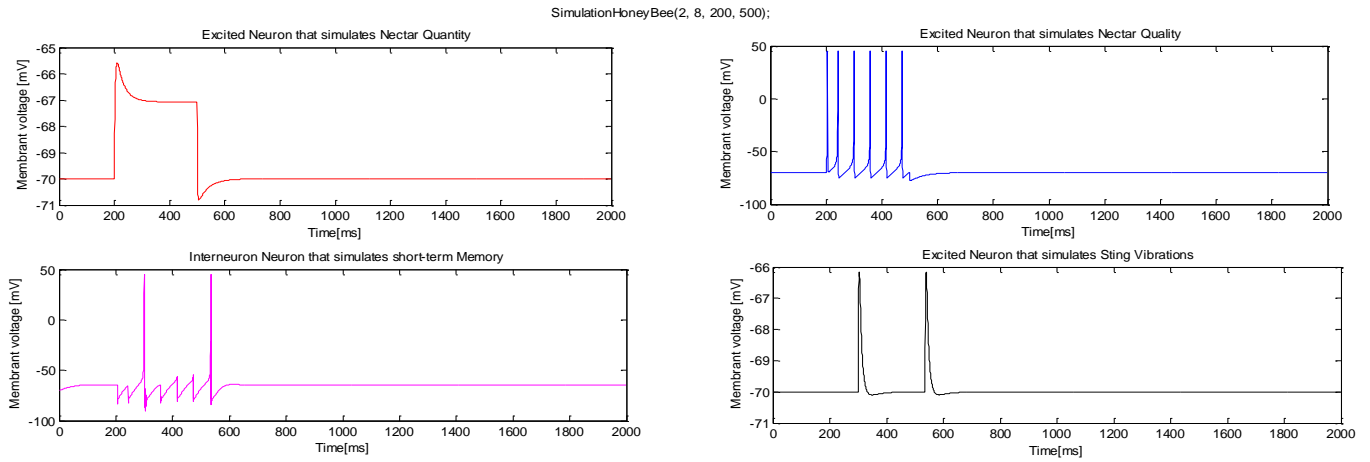


Fig. 6: Criteria 2: quantity is low, and quality is high.

Matlab function "SimulationHoneyBee" is called with parameters where quantity of food sources was fed as 2, quality of food source was fed as 8, for the period of 300 ms.

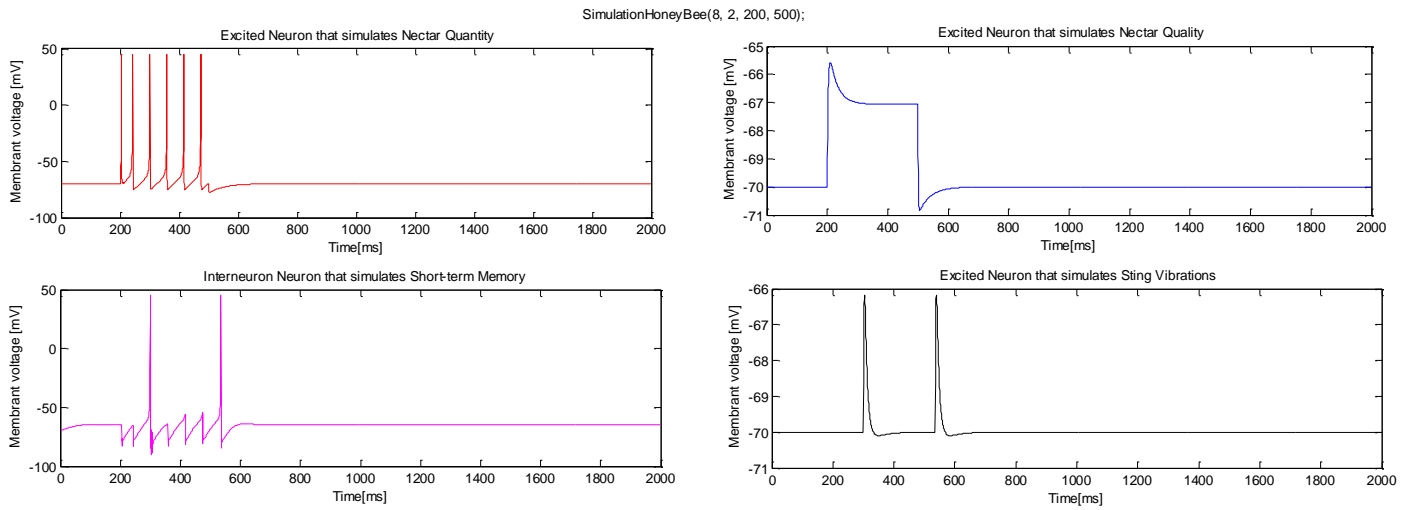


Fig. 7: Criteria 3: quantity is high, and quality is low.

Matlab function "SimulationHoneyBee" is called with parameters where quantity of food sources was fed as 8, quality of food source was fed as 2, for the period of 300 ms.

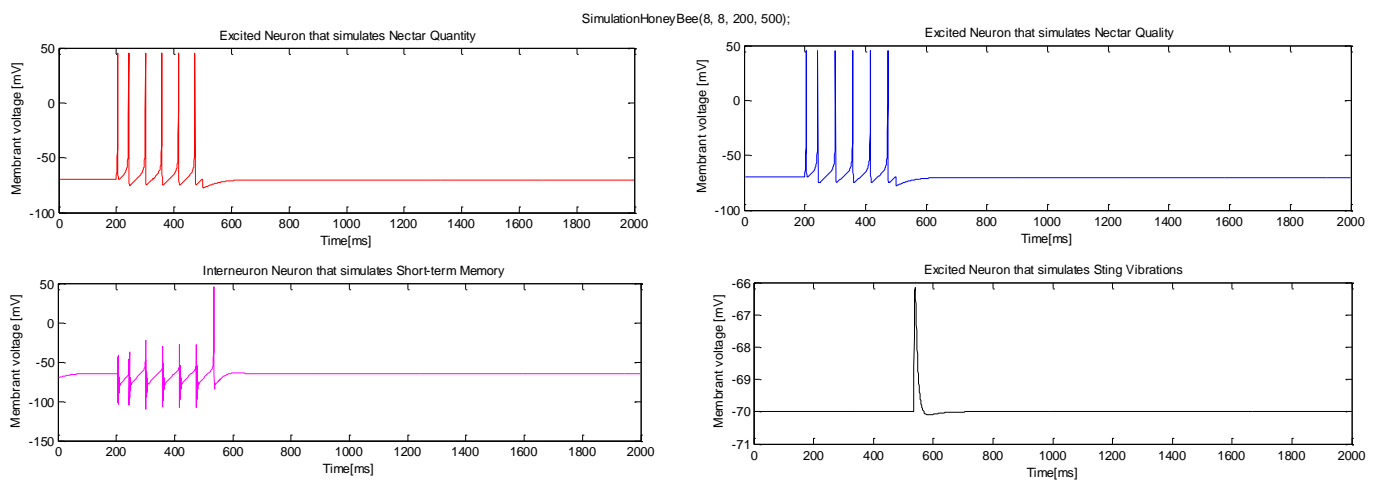


Fig. 8: Criteria 4: quantity is high, and quality is high.

Matlab function "SimulationHoneyBee" is called with parameters where quantity of food sources was fed as 8, quality of food source was fed as 8, for the period of 300 ms.

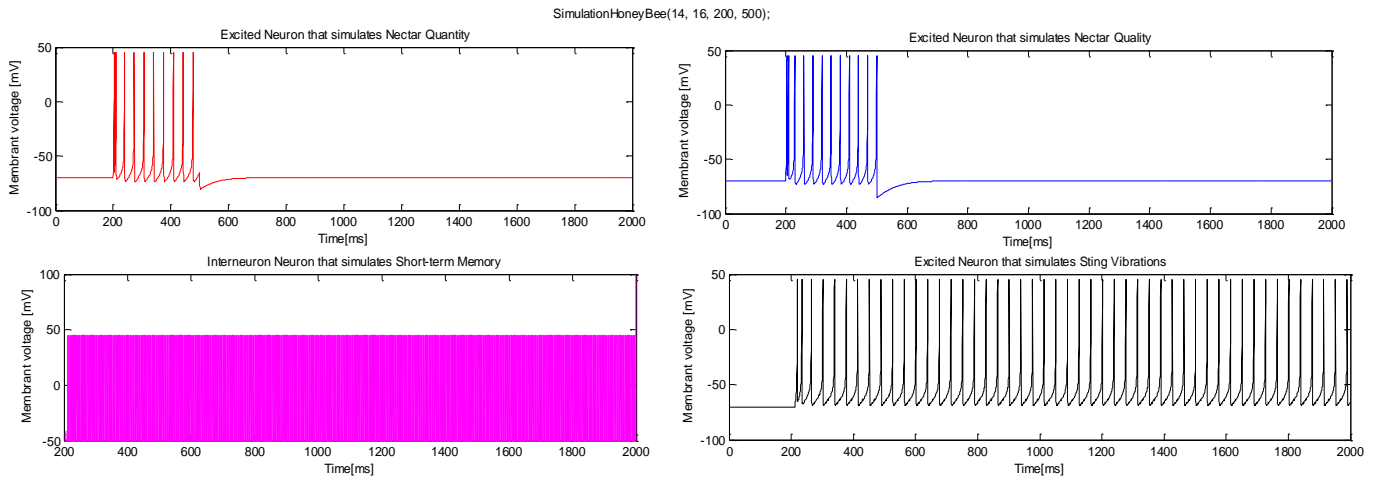


Fig. 9: Criteria 5: quantity is very high, and quality is very high, for a shorter period of time.
 Matlab function "SimulationHoneyBee" is called with parameters where quantity of food sources was fed as 14, quality of food source was fed as 16, for the period of 300 ms.

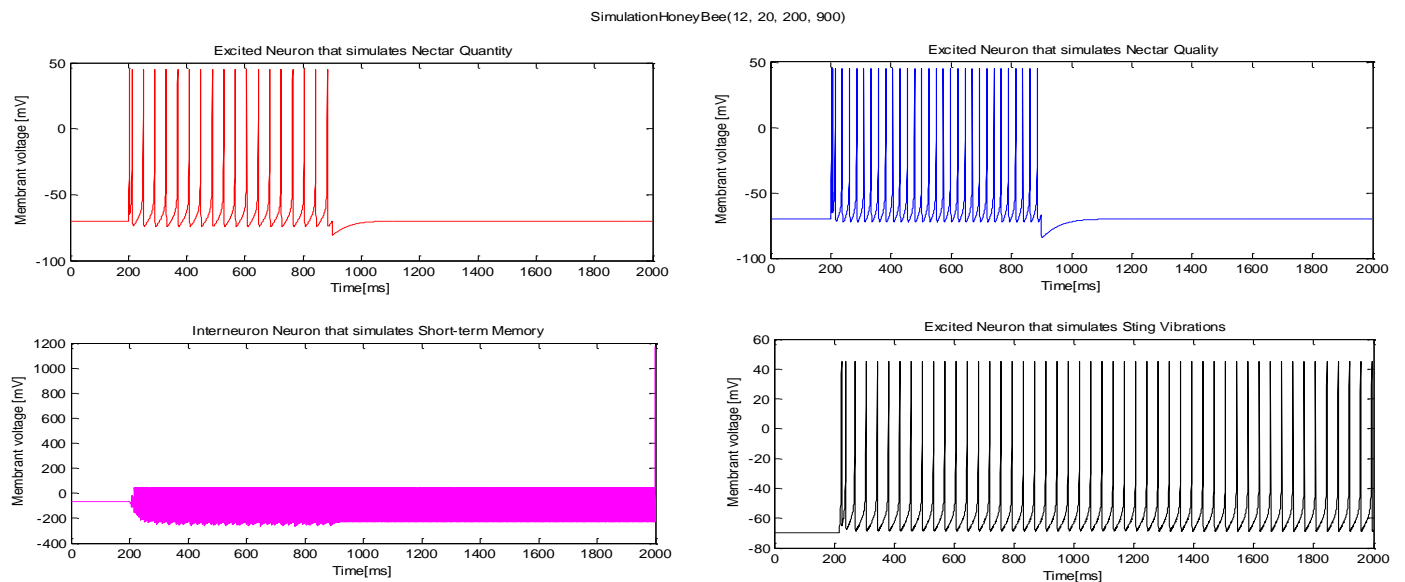


Fig. 10: Criteria 6: quantity is very high, and quality is very high, for a longer period of time.
 Matlab function "SimulationHoneyBee" is called with parameters where quantity of food sources was fed as 14, quality of food source was fed as 16, for the period of 700 ms.

6. DISCUSSION

The figures (from figure.5 to figure.9) depict the change of membrane potential as we change the rate of applied external current to excitatory sensory neurons (neuron that senses quality and neuron that senses quantity). When the rate of applied external current is significant to a particular sensory neuron that neuron has generated spikes (memory voltage of that neuron has reached to +45 mV).

However, as depicted in these figures, even the applied external current has slightly excited the sensory neurons it has not significant enough to excite the interneuron through these excitatory neurons when the rate of the applied current is very low (see figures 5-7). Therefore, interneuron has failed to excite the motor neuron and thereby the motor neuron has unable to perform any sting vibrations. On the other hand, when the rate of the applied current is significant (see figure.9), then it has successfully excited the interneuron and

consequently has enabled the motor neuron also to fire by generating many spikes which results in strong sting vibrations.

Furthermore, when we apply a higher rate of external current for a longer period of time to these excitatory neurons to indicate that higher volume and higher quality of a food source has been found, see figure.10, the motor excitatory neuron has increased the number of sting vibrations. Therefore, we can conclude that the proposed model has the ability to demonstrate honeybee food reporting behavior to their colony according to the abundance of the nectar. In particular, when the quality and the quantity of the food sources are not that significant then these excitations will inhibit the interneuron and thereby no sting vibrations will be produced by the excitatory motor neuron. On the other hand, if we increase the rate of the external current or the duration of the time period the external current has been applied, this

will excite interneuron and subsequently will excite the motor neuron to perform sting vibrations.

As further study the integration of LSTM (Long-Short-Term Memory) structure to model the interneuron is more essential to overcome the issue of tracing and not over-whelming the inter-neuronal memory about the reported food sources at the colony. Interaction of this smaller network (a honey bee) with other similar networks (other honeybees) is needed to be further analyzed so that they will enable themselves to simulate higher cognitive tasks.

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