Neuromorphic Object Tracking Architecture, Based on Compound Eyes, and Implementation on FPGA

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***Abstract*- Recent findings in neuroscience, show that rapid changes in flight direction of a housefly/blowfly (mainly to track objects) are attributable to neural circuits distributed behind its photo-receptors. While tracking objects, using its compound eye structure, a fly is able to detect changes in the motion of the object quickly and changes its own motion accordingly. The working of these neural circuits may be modelled as a set of leaky integrate and fire neurons connected in a special manner to form a competitive feedback control. Based on this knowledge, we present a neuromorphic competitive control circuit utilizing an inference neuron model to control N actuators and analyze their outputs for tracking an object. This model was simulated in software first and then implemented on a Xilinx Artix-7 XC7A35T- ICPG236C FPGA board using Verilog. The results show an observable decoherence phenomenon between the neurons and support the working principle of the model.**

***Index Terms* – Neuromorphic, Competitive Control, Object Tracking, LIF Neuron**

I. INTRODUCTION

Tracking a moving object is an important task and its applications lies in all sorts of operations starting from security to defense activities. In nature, the housefly may be considered as one of the most competent aerobatic pilots. During the pursuit of small targets in both, stationary and moving environments, a housefly is capable of turning about its vertical axis in under 120 ms, at angular velocities up to 4000 deg s^{-1} [1]. However, surprisingly, the computational power of fly's neural circuits is even less than that of a toaster [2]. Additionally, the speed of signals in a fly's neural controller is well below 100m/s [3].

Apart from these, the neural computation is parallel and independent in every circuit corresponding to each receptor. With no central processing unit present, speed of information is almost similar to that of signal and it moves from receptors(eye) to actuators(wings) [4].

A conventional digital control circuit for object tracking and its control mechanism consumes a lot of power and is computationally expensive [5]. Even though control systems in nature are analog, replicating such systems using an analog computer is significantly complex [6]. Hence, the principles of neuromorphic engineering could be applied for the task of developing biologically inspired control systems [7], [8], [9].

In this paper, we implement a compound eye model for object tracking, using leaky integrate-and-fire (LIF) spiking neurons, to build a biologically inspired neuromorphic control system.

II. COMPOUND EYE

The visual system of a fly comprises compound eyes and the motion information produced. This visual system helps the flies to orient quickly during their flight. Studies

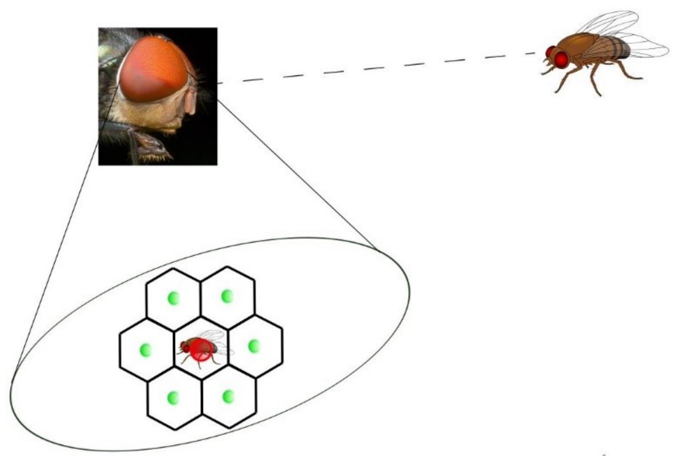

Fig. 1. Ideal orientation (center position) of a fly's compound eye while tracking an object. The figure depicts the compound eye structure when a fly's gaze is on the object being tracked.

suggest that the fly's flight control commands originate from a few hundred neurons in its brain. The neural processing involved is imperative for flight control and object tracking. Each of the fly's compound eyes is composed of up to 6000 miniature hexagonal eyes, or ommatidia. Each ommatidium measures light intensities within a small solid angle of 1 to 2 degrees [2].

The ommatidium operates in conjunction with its neighbors, which together constitutes the elementary motion detectors(EMD). Even though each ommatidium sees only a little bit of the surroundings, its view is compared with its neighbors', and if the views are different, the fly senses movement [2].

In addition, while tracking an object, the fly orients itself in such a way that the tracking object is always around the center of the compound eye for proper operation as shown in Fig. 1. In our model, for the purpose of modelling the compound eye made up of 9 ommatidium structures and each ommatidium made up of a single sensory neuron unit is assumed and is discussed further in the following sections.

III. THE LEAKY INTEGRATE-AND-FIRE (LIF) NEURON

The whole operation of the compound eye model is designed using Neuromorphic Competitive Control (NCC). Inside each individual NCC block, the LIF neuron model is the main building block.

This LIF neuron can be modelled with one input, one output, and one internal signal. Based on the input signal value, the internal signal will increase dynamically and in absence of an input signal, the internal signal will show leaky behavior with some time constant.

Whenever, the internal signal reaches a threshold value, the output will be 1 (i.e., firing of neuron) and the internal signal will be set to 0 again as shown in Fig. 2.

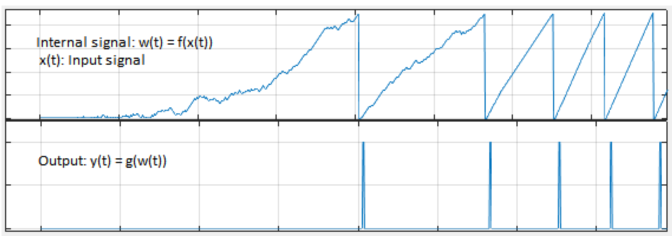

Fig. 2. Behavior of the leaky integrate-and-fire (LIF) neuron model

IV. WORKING OF THE COMPOUND EYE BASED ON NEUROMORPHIC COMPETITIVE CONTROL

The compound eye of a housefly can be modeled as a bunch of hexagonal structures (ommatidia). The internal control circuit behind each of the individual ommatidium can be realized as a competitive control circuit based on the LIF neuron model as depicted in Fig. 3A and Fig. 3B.

This internal circuit as shown in Fig. 3B. consists of three parts. The first or central part is mainly the LIF model, which will emit a pulse based on the input being fed into it (Fig. 2). The second part is the secondary neuron model responsible for membrane potential adjustment, and the last one is the inference neuron-based feedback circuit. When a particular receptor (ommatidium) is not-blocked i.e., no object is present in front of it, the corresponding LIF model will emit spikes rigorously. However, if the ommatidium is off, the frequency of spike generation will be very low and as soon as it becomes turned on, frequency will be increased significantly.

The secondary neuron block mainly controls ‘input to the corresponding LIF (i.e., Membrane Potential)’ and ‘driving signal’ for that receptor. Input to this block is the spikes generated by the corresponding LIF block and the feedback input given by the inference neuron (indicated as ‘U’ in Fig. 3B.).

The feedback loop mainly consists of an inference neuron(Fig.4). Spikes generated by each LIF block of all the receptors are passed onto the inference neuron based on the presence of any obstacles in front of it. After which, logical OR operation is performed on the signals. This feedback signal is fed into the secondary neuron block of all the receptors individually.

Hence, multiple number of LIFs are connected, such that the

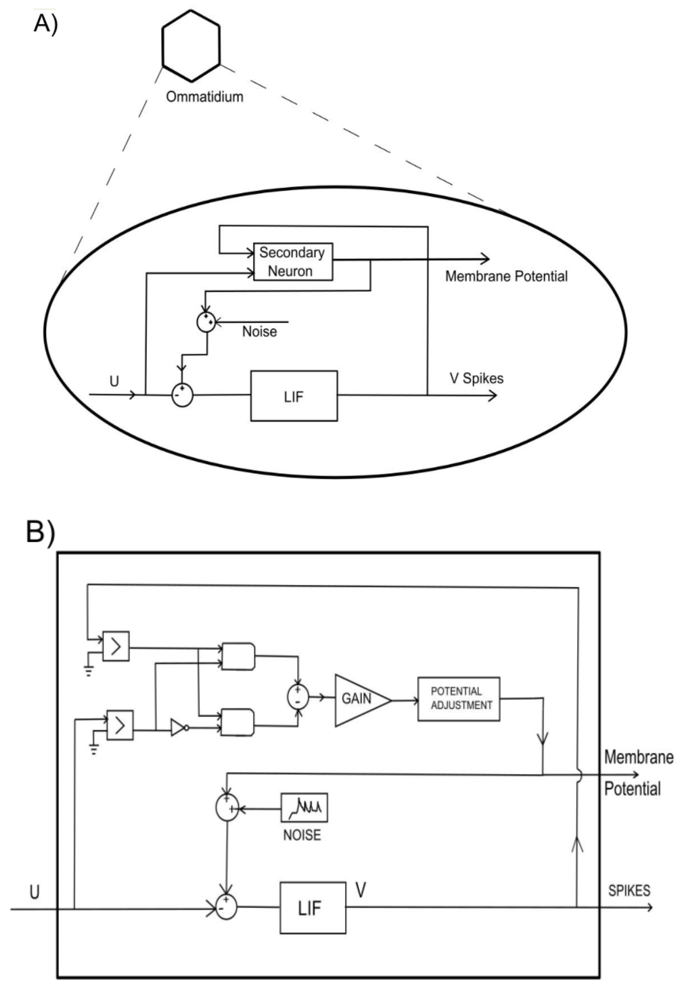

Fig. 3. Model of the compound eye of a housefly, based on neuromorphic competitive control. **A.** Developed sensory block model behind each receptor of the compound eye (ommatidium) of a housefly. **B.** Elaborate model of a single sensory block with the LIF and secondary neuron

spike emitted by each is given as negative feedback to the input of the rest. Due to this mutual inhibition, few interesting organized behaviors such as decoherence and random spreading are observed [5].

As indicated in Fig. 3B, the added random noise towards the input of the LIF neuron is responsible for random spreading. This makes sure that the probability of multiple LIF firing at the same time instant is quite low, which in turn gives rise to decoherence, an interesting phenomenon from the neuro-computational point of view. Irrespective of being de-centralized, this ability of the LIF network to decohere makes it possible to effectively sample the network’s external environment.

When a fly is trying to track an object in front of it, ideally it should be blocking the central receptor. Hence, the energy of the central circuit will be quite low and the spikes also should be of very low frequency. However, if the object moves or changes its course, then the central receptor will not be blocked anymore and some other receptor which was unblocked previously will be blocked.

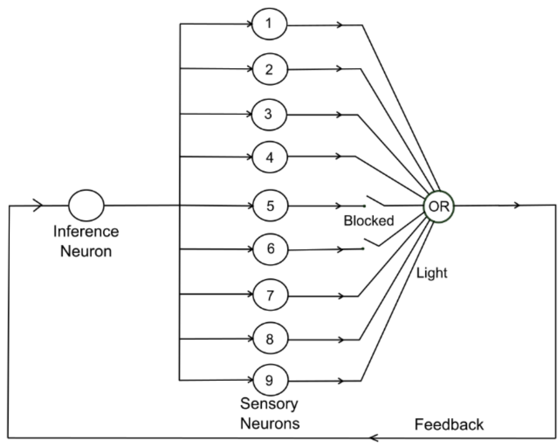

Fig. 4. Top level block diagram with 9 sensory neurons, with the fifth neuron being central.

Hence, the output of this receptor will be similar to that of the receptor which is unblocked and spikes will be more frequent. By monitoring the spikes of different receptors, the direction in which the object has moved and its instantaneous position can be estimated. Based on this information, the whole structure moves and again aligns itself in such a way that the object position comes back to the center of the structure and the central receptor gets blocked again.

V. Results

Based on the functionality of the compound eye as described, the variation of the receptors spiking during object tracking and the corresponding positioning for obtaining a centered response is modelled using MATLAB.

The model of the compound eye depicts the movement of the elementary motion detectors (EMD) while tracking the object. The presence of an object is determined by the reduced spiking of the corresponding EMD and corresponding to every instantaneous position of the object,the model is aligned to the center EMD . In Fig. 5, the red dots denote the 8 neighbouring EMD's and the green star denotes the object being tracked. With the movement of the object ,the model is moved as a whole and is aligned or centered to the object. The object movement is shown as random .The trajectory of the movement of the model is depicted through black lines.

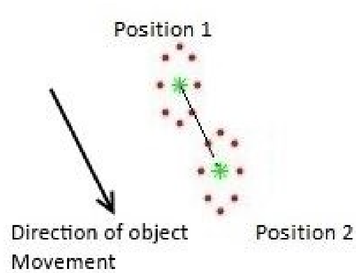

Fig. 5. Displacement of the compound eye model to track a target object.

In the model, the target is moved in a random trajectory and hence, the compound eye also moves, thereby tracking the object. Fig. 6 shows the overall movement of the object and the final position of the model.

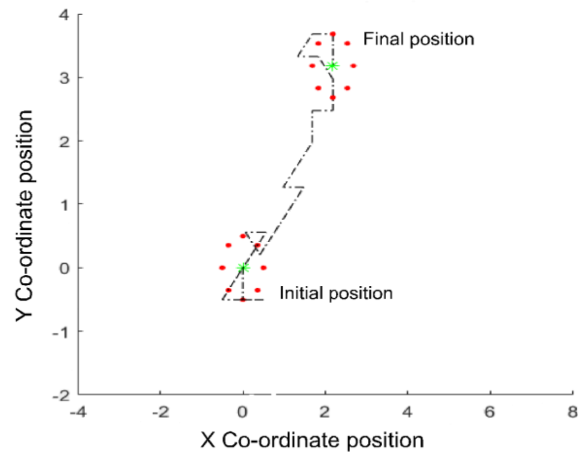

Fig. 6. The object tracking mechanism of the model, indicating the final and initial position along with detailed trajectory of a target object.

The working circuit for this model is also implemented on FPGA. For the simulation, we assumed that the compound eye structure consists of 9 receptors and hence, 9 such competitive control circuits (sensory neurons) will be associated with it. The neurons are numbered from 1 to 9 with '5' being the central receptor, as shown in Fig. 4.

Here the assumption is that the motion of object is not faster than one step of the fly. During simulation, one external 9-bit input was given, indicating the location of object in front of the compound eye. The spikes emitted by the LIF neurons and the membrane potential of the secondary neuron for all 9 blocks are shown in Fig. 7.

To understand the operations, the entire time axis is divided into 13 regions (A, B, C and so on).

As per the neuron alignment, neuron 5 (N5) is the central neuron, indicating that for ideally tracking the object, the 5^{th} receptor should be blocked. However, because of the movement or change in course of the object, some other neurons might get blocked leaving N5 unblocked. To track it properly, the whole structure should be moved in such a direction that N5, i.e., the central receptor should be blocked again leaving the former neuron as unblocked again.

In the beginning (A), the central (5^{th}) receptor was blocked and, hence, the spikes corresponding to it were less frequent compared to those corresponding to other receptors and its membrane potential was also less.

However, in 'B', due to movement of the object, N1 gets blocked and N5 gets unblocked. Hence, the frequency of N5 spikes increases and that of N1 reduces. Also, the membrane potential increases for N5 and decreases for N1.

In region C, the structure moves in appropriate direction to make N5 blocked again, and the same can be verified from the spike and membrane potential curves.

Again, in time interval D, N5 gets unblocked and N9 gets blocked due to object movement. Thereafter, in E, the central neuron becomes blocked again, leaving N9 unblocked.

Similarly, in the sub-sequent cases, due to movement of objects, neurons 6, 4, 3, 7, 2, and 8 get blocked and then again get unblocked, respectively. The frequency of spikes emitted by the LIF neurons and membrane potential of

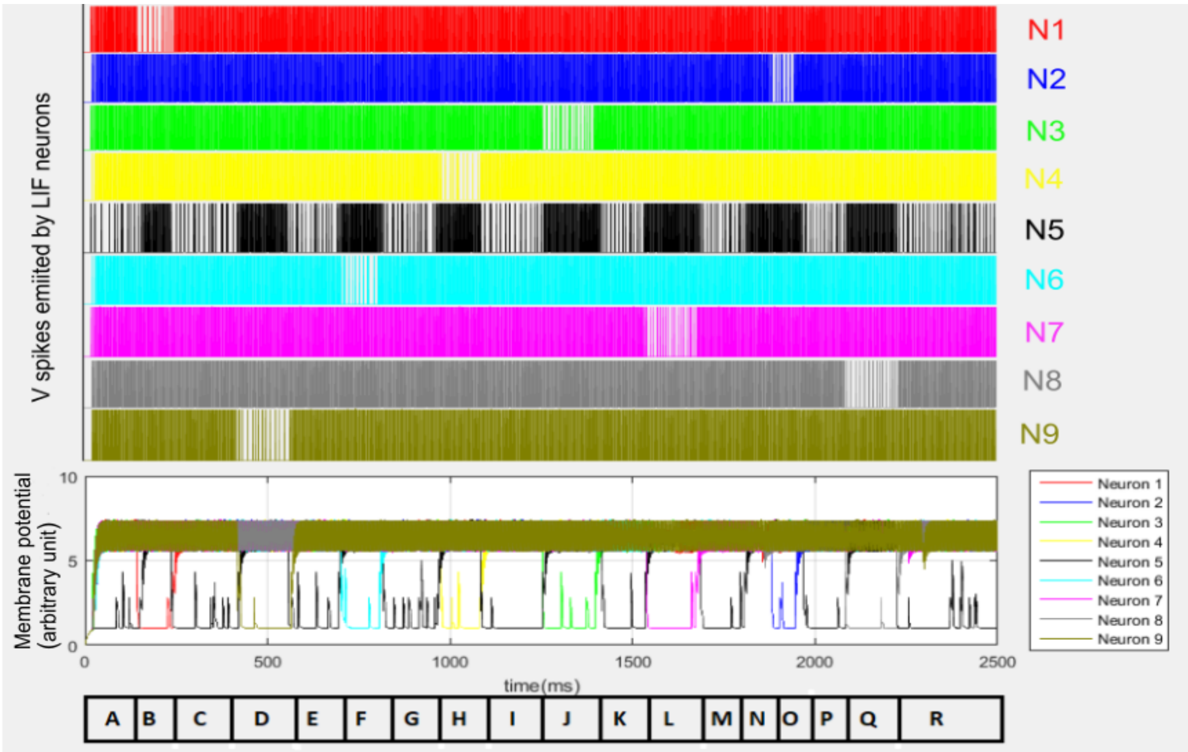

Fig. 7. Spikes emitted by the LIF neurons and membrane potential of secondary neurons in the control block.

secondary neurons corresponding to each one of them describes the complete sequence.

In the FPGA, the simulation is done with 9 neurons and the summary of the utilization report on Xilinx Artix-7 XC7A35T-ICPG236C FPGA is given in Table I. The whole circuit is utilizing nearly 3.6% of all look up tables and 0.9% of all flip flops of the FPGA board.

TABLE I
Utilization Report on Xilinx Artix-7 XC7A35T- ICPG236C FPGA

Resource	Utilization	Available	Utilization %
LUT	758	20800	3.64
FF	369	41600	0.89

VI. Conclusion

In this paper, we have presented a biologically inspired compound eye model for object tracking, which is robust to noise and, varying network size based on the neuron model. We have demonstrated the functionality of the compound eye model and its object tracking mechanism using MATLAB simulations and its implementation on an FPGA board. The resource utilization of the entire system is very low, which favors the implementation in silicon, for real- world applications of object tracking in the area of computer vision.

Acknowledgment

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