Computational model of the LGMD neuron for automatic collision detection

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***Abstract*—In many animal species it is essential to recognize approach predators from complex, dynamic visual scenes and timely initiate escape behavior. Such sophisticated behaviours are often achieved with low neuronal complexity, such as in locusts, suggesting that emulating these biological models in artificial systems would enable the generation of similar complex behaviours with low computational overhead. On the other hand, artificial collision detection is a complex task that requires both real time data acquisition and important features extraction from a captured image. In order to accomplish this task, the algorithms used need to be fast to process the captured data and then perform real time decisions.**

Taking into account the previous considerations, neurorobotic models may provide a foundation for the development of more effective and autonomous devices/robots, based on an improved understanding of the biological basis of adaptive behavior. In this paper, we make a comparative analysis between the new computational model of a locust looming-detecting pathway and the model previously proposed by us. The obtained results proved the improvement provided by the pixel remapping in the model performance.

I. Introduction

Visually evoked collision avoidance behaviors are critical for the survival of many animals. Due to the robustness, naturality and probability of the visually evoked escape responses, they became an excellent tool for studying the neural mechanisms of sensory-motor integration. The neurons that respond selectively to approaching objects have been studied across very different animal species, as humans, pigeons, monkeys, turtles, flies, locusts, among others [1]. From the animals previously mentioned, insects, as flies and locusts, are particularly interesting from an engineer point-of-view: many insects are able to perform, fast and robustly, different behaviours, despite their low-resolution vision and limited neural resources.

The mechanisms of collision detection have been well studied in the locust collision-avoidance response [2]. In this insect, the Lobula Giant Movement Detector (LGMD) is a bilaterally paired motion sensitive neuron that integrates inputs from the visual system, responding robustly to images of objects approaching on a collision course, being responsible for triggering collision avoidance behaviours in locusts [3], [2].

The first physiological and anatomical LGMD neuron model was developed by Bramwell in [4]. The model continued to evolve [5], [7], [8], [6] and it was used in many applications for collision detection. However, further work is needed to develop more robust models that can account for complex aspects of visual motion.

In this article, we extend our previous LGMD model[9] which was able to achieve noise immunity[6] and direction sensitivity [8]. We propose to improve over the existing LGMD model by introducing a novel pixel mapping on the captured image that feeds the neural network.

This new remapping is based on the ommatidia distribution in the locust compound eye. In the locust compound eye, there are variations in local angular sampling density, with some regions having higher resolution than others[10]. This preprocessing enables a considerable reduction of redundant high-frequency information from the peripheral regions, without a subsequent loss of perceptual information. Along this paper, we will highlight the main advantages of the image remapping when integrated in the artificial LGMD model already proposed by us in [9].

In the future, this bio-inspired control algorithm could be applied in very different fields: ranging from medical to automobile applications.

II. Proposed LGMD neural network

The biological inspired neural network here proposed (figure 1) is based on previous models described on [6], [8].

It is composed by five groups of cells: photoreceptor cells (P layer), excitatory cells (E layer), inhibitory cells (I layer), summing cells (S layer) and noise reduction cells (NR layer). Besides that, it is composed by five single cells: the direction sensitive system, composed by the approaching cell (A cell), the receding cell (R cell) and the direction cell (D cell), the feed-forward inhibition cell (FFI cell) and the LGMD cell.

The first processing step is an innovative approach introduced by us in this paper. A grayscale image of the camera current field of view, represented has a matrix of values (from 0 to 255), is remapped according to two main areas: the fovea, were the pixels maintain the gray level of the original image; and the surrounding visual area, where each pixel takes the value of the average of the surrounding pixels (see figure 2). The main advantages added by the remapping processing are concerned to: 1) Increase the performance of

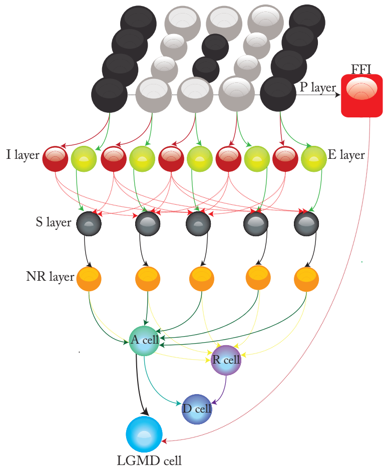

Fig. 1. Schematic illustration of the proposed LGMD model.

the LGMD model when presented with high noise levels, by attenuating considerably high-frequency information from the peripheral regions; 2) Reduce the computational cost of the entire algorithm, by decreasing the number of individual pixels in the image.

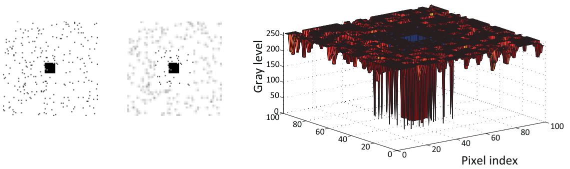

Fig. 2. Image retinal remapping. Left: Original simulated image of an approaching black square, with 500 pixels of noise. Middle: remapped image following the spatial ommatidia distribution in the locust compound eye. Right graph: surface of the remapped image, showing the gray level difference between the fovea and the surrounding area.

Then, the output of this redistribution is transmitted to the P layer. This layer calculates the absolute difference between the luminance of the current and of the previous input images, mathematical represented by the following equation:

$$P_f(x,y) = \left| L_f(x,y) - L_{f-1}(x,y) \right| \tag{1}$$

where $P_f(x,y)$ is the output relative to the cell in the *(x,y)* position at frame f , $L_f(x,y)$ and $L_{f-1}(x,y)$ are the captured luminance at position *(x,y)* for frames *f* and *f-1* , respectively. The output of the P layer is the input of two different layers: the excitatory (E) and the inhibitory (I) layer. The E layer captures directly the excitation that comes from the P layer and it is passed directly to the retinotopic counterpart at the S layer. The inhibition layer (or I layer) receives the output of the P layer and applies a blur effect on it, using:

$$I_f(x,y) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} P_{f-1}(x+i, y+j) \cdot W_I(i,j),\ i,j \neq 0, \tag{2}$$

where $I_f(x,y)$ is the inhibition relative to the cell in the *(x,y)* position at frame *f*, $W_I(i,j)$, an empirically set kernel, represents the local inhibition weight. Finally, the excitatory flux from the E cells and the inhibition that comes from the I cells are summed by the S cells (summing cells), using the following equation:

$$S_f(x,y) = E_f(x,y) - w_i.I_f(x,y),\ E_f(x,y) = P_f(x,y), \tag{3}$$

where w_i(a scalar) represents the inhibition strength. Based on [6], a new mechanism for the LGMD neural network was added to filter background noise. This mechanism, implemented in the NR layer, takes clusters of excitation in the S units to calculate the input to the LGMD membrane potential. These clusters provide higher individual inputs then the ones of isolated S units. The excitation that comes from the S layer is then multiplied by a passing coefficient Ce_f, whose value depends on the surrounding neighbours of each pixel, calculated as follows:

$$Ce_f(x,y) = \frac{1}{9} \sum_{i=-1}^{1} \sum_{j=-1}^{1} S_f(x+i, y+j) \tag{4}$$

The final excitation level of each cell in the NR (Noise-Reduction) layer, at frame f (NR_f), is given by:

$$\begin{aligned} \mathrm{NR}_f(x,y) &= |S_f(x,y).Ce_f(x,y).w^{-1}| \\ w &= \max(|\mathrm{Ce}_f|)C_w^{-1} + \triangle c \end{aligned} \tag{5}$$

$C_w$is set to 4, Δc is a small number (0.01) to prevent w from being zero, and $\max(|Ce_f|)$ is the largest element in matrix $|Ce_f|$. Within the NR layer, a threshold filters the decayed excitations (isolated excitations), as:

$$\tilde{\mathrm{NR}}_f(x,y) = \begin{cases} \mathrm{NR}_f(x,y),\ \mathrm{if}\, \mathrm{NR}_f(x,y).C_{\mathrm{de}} \geq T_{\mathrm{de}} \\ 0,\ if\ \mathrm{if}_f(x,y).C_{\mathrm{de}} < T_{\mathrm{de}} \end{cases}, \tag{6}$$

where $C_{\mathrm{de}} \in [0,1]$ is the decay coefficient and T_{de} is the decay threshold (set to 20). The decay threshold here used was experimentally determined. The NR layer is able to filter out the background detail that may cause excitation. The LGMD potential membrane K_f, at frame *f*, is summed after the NR layer,

$$\mathrm{LGMD}_f = K_f = \sum_{x=1}^{n} \sum_{y=1}^{m} (\tilde{\mathrm{NR}}_f(x,y)), \tag{7}$$

where n is the number of rows and m is the number of columns of the captured image. The A (Approaching) and R (Receding) cells (modified from [8]) are two grouping cells for depth movement direction recognition. The D cell or Direction cell ($\in \{-1,0,1\}$ in case of receding, no movement and approaching object, respectively) is used to calculate the direction of movement (for further details, see our previous paper [9]). The LGMD membrane potential K_f is then transformed to a spiking output $k_f \in [0.5,1]$ using a sigmoid transformation,

$$k_f = (1 + e^{-K_f \cdot ncell^{-1}})^{-1}, \tag{8}$$

where ncell is the total number of cells in the NR layer. The collision alarm is decided by the spiking of the LGMD cell. A spiking mechanism was implemented using an adaptable threshold. This threshold starts with a value experimentally determined, $T_s(0.88)$ and it is updated at each frame, through the following process,

$$T_s = \begin{cases} T_s + \triangle t, \text{ if } s_{av} > \Pi \text{ and } (T_s + \triangle t) \in [T_l, T_u] \\ T_s - \triangle t, \text{ if } s_{av} < \Pi \text{ and } (T_s - \triangle t) \in [T_l, T_u] \\ T_s, \quad \text{others} \end{cases}, \tag{9}$$

where $[T_l, T_u]$ defines the lower and upper limits for adaptation (T_l is 0.80 and T_u is 0.90) , Δt =0.01 is the increasing step, Π =0.72 is a threshold that limits the averaged spiking output s_{av}, between frame *f-5* to frame *f-2* ,

$$s_f = \begin{cases} 1, \text{if } k_f \geq T_s \textit{ and } D = 1 \\ 0, \text{ others} \end{cases} \tag{10}$$

Finally, a collision is detected when there are n_{sp} spikes in n_{ts} time steps ($n_{\text{sp}} \leq n_{\text{ts}}$) , where n_{sp} is 4 and n_{ts} is 5 (values experimentally determined).

$$C_f = \begin{cases} 1, \text{ if } \sum_{f-n_{\text{ts}}}^{f} s_f \geq n_{\text{sp}} \\ 0, \text{ others} \end{cases} \tag{11}$$

The escape behavior is initialized when a collision is detected. Besides that, the spikes can be suppressed by the FFI cell when whole field movement occurs. The FFI cell is a cell which is very similar to the LGMD cell but receives the output from the P layer, as follows:

$$\text{FFI}_f = \frac{\sum_{x=1}^{m} \sum_{y=1}^{n} |P_{f-1}(x,y)|}{\text{ncell}}, \tag{12}$$

If FFI_f exceeds a threshold T_{FFI} (experimentally set to 25), the spikes produced by the LGMD cell are automatically inhibited. As described in this section, the proposed LGMD model only involves low level image processing, being independent of object classification.

III. Results and Discussion

In a way to test the efficiency of the LGMD neural network proposed, two experimental scenarios were used. The first experiment was made on a simulated data set and, in the second, we used a recorded video to prove the capacity of the LGMD neural network to work in a real environment. In the first experiment, we subjected the model previously proposed by us in [9] and the new LGMD model to the same visual stimuli, in order to evaluate the performance improvement provided by the novel pixel remapping here introduced, relative to: immunity to highly noisy environments and reduction of the model processing time.

A. Simulated Environment: Development and Results

We developed a simulation environment in Matlab, which enables us to assess the effectiveness of the proposed LGMD neural network. Objects were simulated according to their movement and the corresponding data was acquired by a simulated camera and processed by the LGMD neural network. Image sequences were simulated and by an artificial camera with a field of view of 60 in both x and y axis, and a sampling frequency of 100 Hz. The computer used was a Laptop (Toshiba Porteg R830-10R) with 4 GHz CPU and Windows 7 operating system.

We used four different simulated visual stimuli to fed our neural network. All the visual stimuli are composed by a black approaching square, with a ratio between object size (l) and velocity (v) equal to 50 milliseconds, over a white background, only varying the noise level in the image sequence, as well as the approaching angle. By varying the parameters between different stimuli, we pretend to analyze the advantages of the remapped image previously mentioned, as well as to test the robustness of the model to approaching objects located outside the remapped "acute zone". For that, the following visual stimuli were generated: *Stimulus 1:* 500 noise pixels added to the image sequence, corresponding to 5% of image pixels ; *Stimulus 2*: 1000 noise pixels added to the image sequence, corresponding to 10% of image pixels. *Stimulus 3:* 500 noise pixels added to the image sequence and an approaching angle 50 degrees deviated from the image center. *Stimulus 4:* 1000 noise pixels added to the image sequence and an approaching angle 50 degrees deviated from the image center.

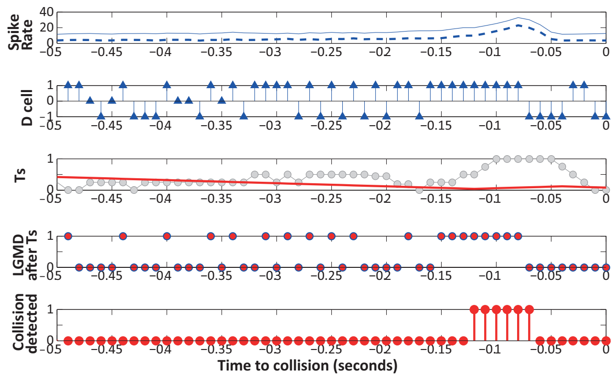

Fig. 3. LGMD model response to *Stimulus 1*. Spike Rate: Blue dash graph: is obtained by the ratio of the A cell value and the total number of cells in the NR layer, produced by the new LGMD model; Blue continuous line: produced by the previous LGMD model proposed in [9]. D cell: output of the direction cell: 1: approaching, 0: no significant movement, -1: receding. Ts: adaptive threshold represented by the red line; the gray points represent the *sav* output. LGMD after Ts: represents the output of the LGMD cell after the application of the threshold *Ts* and taking into account the output of the D cell. Collision detected: the output of this graph is one when it is detected four successive spikes in five successive time-steps. In all these graphs, the zero value corresponds to the time of collision.

Figure 3 represents the output of the LGMD model when stimulated with *Stimulus 1*. In this figure, at each time step we can observe the result of different mathematical processing (described in section 2). In the top graph, it is represented the spike rate of the previous LGMD model proposed [9] by a continuous line and the spike rate of the new proposed model is represented by a dashed line. Observing both graphs, we automatically notice a big difference between the mean spike rate produced by each different LGMD model. At *t=-0.5* seconds, the existing spikes are mainly a result of the excitation produced by noise pixels. By this reason, we notice that the new LGMD model is more robust to the noise presence because the excitation level produced by the noise pixels is very low compared to the previous model [9]. This fact will decrease the probability to wrongly detect collisions.

In order to make a clear comparison between both LGMD models, we evaluate their performance by measuring: the processing time (*P.time*), the Mean Spike Rate in the A cell produced as a response to noise (*MSR*) as well as the distance at which the LGMD models detected collisions (*Coll. D.*) .

Relatively to the other simulated visual stimuli, table I summarizes the obtained results.

TABLE I
RESPONSES OBTAINED WITH LGMD MODEL [9] AND LGMD MODEL HERE PROPOSED.

	Previous model			Proposed model		
STIM.	P.time	MSR	Coll. D.	P.time	MSR	Coll. D.
1	0.020	13.2	15 cm	0.018	7.15	11 cm
2	0.022	13.3	18 cm	0.020	7.25	11 cm
3	0.038	22.7	84 cm	0.028	10.1	12 cm
4	0.039	22.8	78 cm	0.029	10.1	11 cm

According to this table, we observe a significant difference between the results (*P.time, MSR* and *Coll. D.*) obtained with the previous and the current LGMD model. In all the situations tested, the processing time and mean spike rate is lower in the proposed model. Additionally, we observe an increase in the noise robustness provided by the new model, which was able to detect collisions (*Coll. D.*) for all the situations tested, when the object was near to the camera ($\simeq$ 11cm, contrary to the previous model which was not able to work correctly in environments with very high noise levels - Stim 3 and 4, detecting prematurely collisions).

B. Real Environment: Registration and Results

In order to test the capability of the proposed LGMD model in a more realistic environment, we subjected it to a real video sequence showing an approaching ball,with $l/v \simeq 30$ ms. A PlayStation Eye digital camera was used to obtain the video clip. The resolution of the video images was 640×480 pixels, with an acquisition frequency of 70 frames per second. The background of the real image sequence is composed by multiple and different static objects.

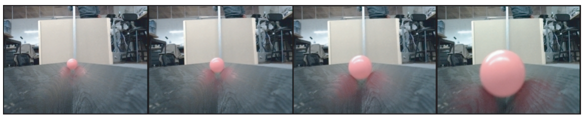

Fig. 4. Selected frames from the recorded image sequence used in the experiment.

Despite the complexity of the environment showed by the real image sequence, both LGMD models were able to correctly detect a collision when the approaching ball was located at 20 cm to the camera. Although, as a consequence of the lower processing time, provided by the remapping introduced in the new model, the model here proposed showed a faster response, which is an important factor for real time applications. With this, we prove the capability of the model to be implemented in a device moving freely within a complex environment.

IV. CONCLUSIONS

In this paper, we propose a modified LGMD model based on the LGMD neuron of the locust brain. This model has a mechanism that remappes the captured images, leading to the improvement of the capabilities shown by a previous model[9]. Using artificial and real image sequences, we showed that the remapping here introduced leads to an increase in the noise immunity of the new LGMD model when compared to [9], which is a very important factor that provides robustness to the model, as well as a decrease in the processing time needed, which is preponderant when a real time response is needed.

The results illustrate the benefits of the LGMD based neural network here proposed, and, in the near future, we are proposed to continue enhancing this approach, using, for that, a combination of physiological and anatomical studies of the locust visual system, in order to improve our understanding about the relation between the LGMD neuron output and the locust muscles related to the avoidance manoeuvres.

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