A bio-inspired visual collision detection mechanism for cars: Optimisation of a model of a locust neuron to a novel environment

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Abstract

The lobula giant movement detector (LGMD) neuron of locusts has been shown to preferentially respond to objects approaching the eye of a locust on a direct collision course. Computer simulations of the neuron have been developed and have demonstrated the ability of mobile robots, interfaced with a simulated LGMD model, to avoid collisions. In this study, a model of the LGMD neuron is presented and the functional parameters of the model identified. Models with different parameters were presented with a range of automotive video sequences, including collisions with cars. The parameters were optimised to respond correctly to the video sequences using a range of genetic algorithms (GAs). The model evolved most rapidly using GAs with high clone rates into a form suitable for detecting collisions with cars and not producing false collision alerts to most non-collision scenes.

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1. Introduction

Locusts are able to detect colliding objects, such as avian predators, using their visual lobula giant movement detector (LGMD) neuron [13,14]. This neuron and the post-synaptic descending contralateral movement detector (DCMD) neuron respond to objects on a direct collision course by producing a burst of spikes which increases in frequency as the object moves closer. The mechanisms used by the neurons to produce this response are well studied and do not involve any of the complex computational tasks such as object identification, velocity estimation or path planning that traditional automotive collision detection processes use (e.g. [3,5]). Computer simulations of the LGMD and its input architecture have shown similar responses to visual stimuli as are shown by the LGMD of the locust, and models coupled with mobile robots have demonstrated an ability to detect and avoid collisions in a simple environment in real time [1,12,15]. Speeds and sizes of colliding objects in automotive situations differ considerably from both natural predators of locusts and obstacles encountered by mobile robots. The use of an LGMD model in an automotive situation would require significant adaptation of the model to its intended tasks.

This study uses a similar model to that of Rind and Bramwell [12] and Blanchard et al. [1] to assess the plausibility of using the locust LGMD as a mechanism for detecting automotive collisions. The key parameters of the model are identified and the model is adapted to the automotive environment by adjusting these parameters with genetic algorithms (GAs). A number of collision and non-collision scenes captured on video are used to evolve the model into a suitable form to detect collisions with cars. The evolved model is then tested using further video sequences to ensure that it can robustly detect collisions and not produce false alerts during non-collision sequences. In addition to looking at the ability of the LGMD model to detect car collisions the efficiency and operation of different GAs are also investigated.
2. Materials and methods

2.1. Overview

A range of video sequences, filmed at 25 frames/s, showing typical automotive scenes and collisions with an inflatable car were selected (Fig. 1). The sequences consisted of two collisions with an inflatable car (8 and 5 s in duration at speeds of 30 and 50 km/h respectively), eight general driving situations including driving over road line markings and turning corners (ranging between 3 and 10 s in duration), and two sequences where cars moved in front of the camera equipped car whilst it was stationary at a junction, herein referred to as translating motion (3 s in duration). These sequences were used as an input into a computer model of the LGMD neuron of the locust (Section 2.2). The parameters of the model were defined by an individual, which was generated by a GA (Section 2.3), and the full range of video sequences were shown to an entire population of individuals. Each individual in the population was designated a fitness based on its collision detection performance to the video sequences. The fittest individuals in the population were used to determine the next generation of individuals (Section 2.3). The process stopped when the fittest individual in the generation responded as required to all of the image sequences or after 1200 new individuals had been produced by the GA (this number did not include cloned individuals—see Section 2.3). The parameters of the individual(s) with the highest fitness were used to further test the model.

The LGMD model and GA optimisation process were written in Matlab 6.5 (The MathWorks, USA) and run on an Intel Xeon 2.4GHz computer under Microsoft Windows XP.

2.2. The LGMD model

The LGMD model used in this study uses the same functional processing layers as that used in Blanchard et al. [1]. Images are inputted into the model as 150 functional processing layers as that used in Blanchard et al. [1]. Images are inputted into the model as 150 functional processing layers as that used in Blanchard et al. The sequences contained little excitation if the change in image at time \( t \) is small, and is eliminated by the lateral inhibitory spread at time \( t-1 \). Only when the rate of object expansion exceeds the spread of inhibition, for example near the point of collision, should the S layer contain high levels of excitation [16].

The S units sum directly onto the LGMD (Appendix A: Eq. (A4)). If the LGMD value exceeded a threshold (LGMD\(_{\text{thres}}\), see Table 1) at a given timestep then a simulated spike was produced by the LGMD. A maximum of one spike per timestep could be produced. A collision detection alarm was triggered if a given number of spikes (spike\(_{n}\)) were produced in a given number of timesteps (spike\(_{\text{delay}}\)). In addition, a separate inhibitory pathway (feed-forward inhibition) was formed by summing the outputs of the photoreceptive units. If the feed-forward inhibition passed a certain threshold (FF\(_{\text{thres}}\)) then it produced an inhibitory response on the LGMD neuron [9,11] (but see [6] for an alternative role of the feed-forward pathway). The feed-forward inhibition response was delayed by a certain number of timesteps (FF\(_{\text{delay}}\)) and was simulated by producing a spike value of \(-1\) in the LGMD.

2.3. The genetic algorithm

The GA used in this study is based on a publicly available Matlab toolbox [2]. The parameters for each individual of generation 1 (\( n = 40 \)) are randomly generated from a uniform distribution within the limits set in Table 1. Each individual is converted into LGMD model parameters and evaluated for each of the video sequences.

Fitness values for each individual began at 0 and for each collision sequence five units were subtracted from the fitness of each individual if it failed to detect the collision at least one video frame (0.04 s) before collision. This would allow sufficient time to create collision mitigation responses such as pre-tensioning of seatbelts, activation of crumple zones in the car or deploying external airbags for pedestrian safety. For each of the non collision sequences 1 unit was subtracted from the fitness of an individual if a false collision was detected and 0 units if no collision was detected. The minimum fitness value for an individual would be—20 units and the maximum would be 0. The difference in fitness values for predicting the wrong outcome between a collision scene and a non collision scene helped the GA avoid parameters such as very high thresholds for the LGMD where all situations including both collisions would be suppressed, and the LGMD model would be functionally useless.

After being evaluated in relation to their fitness, a percentage of individuals with the highest fitness are cloned and the clones enter the next generation unchanged. These cloned individuals do not need to be tested in the next generation, since the optimisation sequences do not
Fig. 1. Frame-grabs from examples of automotive video sequences used to optimise and test the model. All sequences were taken from a digital video camera mounted on a tripod inside a car. Sequences were taken at 25 Hz. Frame-grabs (i, a–e) were taken from some of the sequences used to optimise the LGMD model. Frame-grabs (ii, a–e) are taken from sequences used to test the model. Sequence (i, a) shows a collision with an inflatable car at 30 km/h. Sequence (i, b) indicates lane changing in close proximity to other moving vehicles. Sequence (i, c) shows the car with the video camera stopped at a junction while a car passes (translates) in front of it. Sequence (i, d) shows rapid rotational movement as the car turns a tight corner at speed. Sequence (i, e) shows a typical driving scene, with other traffic and road lines present. Sequence (ii, a) shows a collision with a polystyrene block at 30 km/h. Sequence (ii, b) shows a further translation scene. Sequence (ii, c) shows the car driving over road lines and pedestrians in the field of view. Sequence (ii, d) indicates travelling on a road with cars approaching in the opposite direction. Sequence (ii, e) shows a further rotational motion situation whilst the car is turning a corner.
change, and are not referred to as new individuals in the results. The remainder of the next generation are generated through crossover and mutation. In this study three rates of cloning were investigated, where the fittest 80%, 50% or 20% (32, 20 or 8 individuals, respectively) of the population were cloned. The fittest individuals in the previous generation produce offspring via crossover to bring the population size back to 40 individuals. For example, if 80% of individuals were cloned then the fittest 20% of individuals in the current generation would produce the remaining 20% of the next generation population through crossover. During crossover the chromosomes containing the six parameters of two individuals are cut in a randomly determined position so that offspring 1 inherits \( x \) parameters from parent 1 and \( y \) parameters from parent 2. Offspring 2 will then inherit \( y \) parameters from parent 1 and \( x \) parameters from parent 2 (where \( x \) and \( y \) are integers between 0 and 6 and \( x + y = 6 \)).

Mutation then occurs on the offspring produced by crossover. Initially 20% mutation was used to test the three different clone rates. The best clone rate (see results) was then tested with three mutation values: 50% mutation, 20% mutation and 5% mutation. Mutation occurs by representing the parameters in binary form, each parameter occupying 10 bytes of memory. The relevant percentage of the binary code for each parameter is selected at random and values swapped (0 values converted to 1 and vice versa).

These processes of cloning, crossover and mutation produce a new generation of individuals \((n = 40)\) which are evaluated in the same manner as before and the process continues for a total of 1200 new (non-cloned) individuals or until an individual with maximum fitness (fitness = 0) is produced. Three replicate rounds of tuning took place for each clone rate and mutation rate tested.

### 3. Results

#### 3.1. The effect of clone rate and mutation rate on the performance of the genetic algorithms

The performance of the different GAs needed to be evaluated with respect to the best individual produced, as this would provide the parameters for the tuned LGMD model, and with respect to the speed in which the solution to the optimisation problem occurred. Although the number of generations is an important consideration in

<table>
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<th>Accuracy</th>
<th>Mean value over 12 trials</th>
<th>Standard deviation</th>
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A full mathematical description of the role of the parameters in the LGMD model is given in Section 2.2 and the Appendix A. The initial range in which the parameters of the model were randomly selected from is given as is the accuracy required from the parameters and the mean and standard deviation of the replicate sets of optimal parameters produced by the GA.
how well a GA performed it does not give a true indication of the time taken to optimise a problem. GAs with high clone rates pass a high number of individuals with identical solutions into the next generation, in this study each individual in each generation was presented with an identical set of challenges or video sequences, as such it is not necessary to re-test unchanged, cloned, individuals and this dramatically speeds up the time taken to test a generation of individuals. As such, fitness values are presented for time against the total number of new (non-cloned) individuals produced.

None of the GAs tested produced an individual with a fitness of zero; however, all of the replicates of all the different clone rates at 20% mutation produced fitness values of −3. Analysis of the results showed that the optimised parameters predicted both collision sequences and only wrongly predicted a false collision alert in three of the 10 non-collision tuning video sequences. The rate of artificial evolution of the LGMD network with 80% clone rate was more rapid, with respect to the number of new individuals, than with the 50% clone rate or 20% clone rate, both for the fittest individual (Fig. 3a) and for the whole population of individuals (Fig. 3b). Also the population had a higher mean fitness using the 80% clone rate than using the 50% clone rate (Fig. 3b). Since it appeared that the 80% clone rate was the best value to use in terms of speed of the optimisation process and the fittest individuals showed equal fitness to other cloning rates, the 80% cloning GA was tested with further mutation rates.

The 50% mutation rate did not produce individuals with fitness values of −3 or above in any of the replicates. The 5% and 20% mutation rates both produced individuals with fitness of −3. The 20% mutation rate showed a slightly more rapid increase in fitness of the best individual than the 5% mutation rate (Fig. 3c) but the increase in mean fitness of the population was more rapid and produced higher fitness values with 5% mutation than with 20% mutation (Fig. 3d). This may occur because a higher proportion of the individuals produced using the 20% mutation rate were badly adapted to the optimisation problem, although at least one individual in the population was well adapted.

The combined GAs produced a total of 12 replicate best individuals with fitness values of −3, all of which correctly predicted real collisions and predicted false collisions in the same three sequences (see below). The values of all of these 12 sets of parameters will be used to test the LGMD model.

3.2. Collision detection performance of the LGMD model

In all of the replicate rounds of tuning with the maximum fitness of −3 (12 replicate sets of parameters—see above) the false collisions which were not suppressed occurred for both sequences when a translating motion occurred as car passed across the image whilst the car with the video camera was stationary at a junction (Fig. 1c). A false collision was also triggered by one sequence of a car turning a corner (Fig. 1d). The GA did, however, tune the LGMD model to detect collisions with the inflatable car and a simulated person and not to produce collision alerts to a wide range of general driving situations including driving in close proximity to other vehicles, driving over lines and markings on the road and other sequences involving turning corners.

When the tuned LGMD models were tested with a range of similar video sequences to which they were optimised,
similar results were obtained. Collision alerts were obtained to another collision with an inflatable car at a different speed (10 s duration, collision at 40 km/h) and for a collision with a polystyrene block (5 s duration at 30 km/h), representing a pedestrian, for all of the 12 optimised models. False collision alerts were produced when translating motion, caused by cars moving across the field of view, occurred in five out of five test sequences for all optimised models (5 s duration for each video sequence). In test scenes involving normal driving situations, where no cars showing translating motion were present, none of the optimised models produced false collision alerts in 41 min of video footage, including rotational movement when the car turned corners, although the speed of car to radius of corner ratio appeared slightly lower than in the failed optimisation sequence.

The 12 optimised models showed many similarities between their parameters (Table 1). In particular the standard deviations for lateral inhibitory strength (I_strength) and the LGMD threshold (LGMD_thres) were less than 5% of the mean, suggesting these parameters are sensitive to the optimal tuning of the model and are almost identical between the different replicates. The feed-forward inhibition threshold values in all the optimised models were high and none of the models utilised the feed-forward inhibition to prevent false collisions during any of the optimisation or test sequences. As such, as long as the value of the feed-forward threshold was high, so as not to interfere with collision detection there was no selection pressure for it and it played a redundant role in this model. This allowed the feed-forward threshold (FF_thres) and feed-forward delay (FF_delay) parameters to vary greatly between the models with no effect on the model performance, as indicated by the high standard deviation values for the models (Table 1).

The spike number (spikeN) required was either 2 or 3 for all of the models. In most (>85%) of the collision alerts produced in the optimisation and testing of the model the spikes required to produce collision alerts occurred in successive timesteps. As such there was little selection pressure on the parameter spikeN.

Investigations into the functioning of the optimised models showed that the images that are inputted into the model are filtered by the neural network, especially by lateral inhibition, and if no collision is imminent or there are no translating objects then the LGMD receives little or no excitation from the S units (Fig. 4a). During normal driving scenes only minor and intermittent activity is seen in the LGMD, and the activity is well below the LGMD.
respond well to most of the test situations, detecting well to most of the automotive situations in the set of situations. The GA does tune the model to respond using the model defined, the latter being the more likely to produce a solution or because no solution can be obtained require longer than 1200 new, non-cloned, individuals to tune the LGMD model to respond as required to all of the sets of image sequences; this is either because it would be optimised to avoid obtaining a localised mechanism for cars. It is able to effectively alert to the dangers of collision before the point of impact (collisions detected 120–40 ms before impact) and thus is able to provide useful collision mitigation responses such as pre-tensioning of seatbelts or pre-deployment of an airbag (M. Soininen, Volvo Car Corporation, pers. comm.). It is also successfully able to discriminate between collisions and most general driving situations. The major problem encountered by the system is that false collision alerts were produced to objects showing translating motion and occasionally to rapid rotational motion, although is robust to most situations involving rotation or turning. The predator avoidance response of the locust is robust to these types of visual stimuli, producing a characteristically different spike frequency in the DCMD than it would to a potentially colliding predator [15,16]. This may occur because the speed to size ratio of a locust’s predator is much higher than for an approaching car (to obtain a similar ratio car collisions would need to occur with a relative velocity \( \sim 300 \text{ km/h} \)) this means that the change in the size of the image over time, and hence excitation from the photoreceptive units, is much lower for the car collision sensor (R. Stafford, unpublished data). This may make distinguishing between colliding objects and translating objects much more difficult in automotive situations. It is clear that the current LGMD model requires modifications or integration with other mechanisms to prevent the detection of these false collisions in certain situations. However, this study demonstrates that the optimised LGMD network can be a useful tool in detecting automotive collisions, and can distinguish collision situations from a wide range of automotive situations, which may otherwise require far higher levels of computational processing.

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**Appendix A. Mathematical representation of the LGMD model**

Output of the photoreceptive units; input is directly from a frame of an image sequence at timestep \( t \) with each pixel luminance value being mapped to the corresponding photoreceptive unit,

\[
P_{ij}(t) = |L_{ij}(t) - L_{ij}(t-1)|, \quad (A1)
\]

where \( L_{ij} \) is the luminance of the pixel at position \((i,j)\).
Lateral inhibition is represented by a spatial low pass filter,
\[ I_g(t) = [(P_g(t-1) + P_g(t)) \otimes K_{pq}], \quad \text{(A2)} \]
where \( I_g \) is the value of inhibition at position \((i,j)\) and \( \otimes \) denotes convolution and \( K_{pq} \) is a \( 3 \times 3 \) matrix with
\[ K_{pq} = 1/9 \times p,q. \]

The sum cells subtract lateral inhibition from excitation from the photoreceptive units. Inhibition is delayed by one timestep and has a synaptic gain \( I_{\text{strength}} \) which is a tuning parameter of the model,
\[ S_{\theta}(t) = P_{\theta}(t) - I_{\text{strength}} I_g(t-1) \quad \text{where } S_{\theta}(t) > 0. \quad \text{(A3)} \]

The membrane potential of the LGMD is formed by summing the S units,
\[ \text{LGMD}(t) = \sum S_{\theta}(t). \quad \text{(A4)} \]

References


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