Modeling Obstacle Avoidance Behavior of Flies Using an Adaptive Autonomous Agent

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Abstract. In the course of evolution flies have specialized visuomotor programs for tasks like compensating for deviations from the course, obstacle avoidance, and landing, which involve the analysis of visual motion information. In order to test models of the obstacle avoidance behavior in flies, we use computer-simulated agents that evolve parts of their sensor system and sensorimotor coupling with genetic algorithms. During a simulated evolution, these agents specialize a visuomotor program that enables the agents to avoid obstacles.

1 Introduction

The goal of this work is to test models of obstacle avoidance behavior which are based on strategies as they are known in flies by synthesizing artificial agents that act in computer-simulated environments. For our agents, the most important biological insight is that flies navigate mostly by evaluating visual motion information by means of neurons that are tuned to specific motion patterns (matched filters) (Krapp & Hengstenberg 1996). The agent evaluates the visual motion information by two units that integrate the motion detector outputs over large receptive fields on the right and left hemisphere respectively. During a simulated evolution – using genetic algorithms – the agent evolves such that these integration units optimize their spatial sensitivity distribution to visual motion information for the task of obstacle avoidance. The hypothesis is that the resulting integration units are tuned to similar motion patterns like the "matched filter neurons" of flies. Several researchers designed computer-simulated agents as well as mobile robots which use a qualitative measure of visual motion information for obstacle avoidance (e.g., Franceschini, Pichon and Blanes 1992, Duchon and Warren 1994, Neven, Steinlage, Giese and Bruckhoff 1996). These agents, however, mostly use knowledge about their own speed in order to compute the distance to the objects and/or the motion information under the constraint that the robot executes pure translations. Flies, however, neither know their own speed nor execute pure translations. Therefore, we designed agents that do not make use of these constraints.

2 The agent's architecture

On the agent we implemented a simplified model (Fig. 1) of visual information processing, i.e. contrast enhancement, reduction of signal redundancy, signal
amplification, motion detection and evaluation of the motion signals which takes place in the subsequent neural layers lamina, medulla and lobula plate in the visual section of the fly's brain (Laughlin 1987).

*The retina R:* The agent has a horizontal array of sensors with a 360° field of view which scans the visual world at the horizon. The visual input to the sensors is spatially lowpass filtered by Gaussian filters (σ = 3.8°). Like in *Drosophila* (Götz 1964), the sensors have an interommatidial angle of δφ = 4.6°. Hence the array has 78 sensors. The temporal delay due to phototransduction by the fly's photoreceptors is modeled by a temporal lowpass filter L with the time constant τL = 10.0 steps.

*Redundancy reduction and amplification of the signal in the lamina L:* In *Drosophila* large monopolar cells (LMCs) in the lamina are known to be responsible for signal amplification, local contrast enhancements and reduction of redundant parts of the signal (Laughlin 1987). In this work we modeled the temporal aspects of the LMC cells by applying a temporal highpass filter H (τh = 10.0 steps), which eliminates parts of the signal that are steady or slowly changing in time. In a next step the signals are linearly amplified to the full range of 256 grey-level values.

*Motion detection in the medulla M and lobula plate LP:* For motion perception in insects, Reichardt & Hassenstein proposed a detector (Hassenstein & Reichardt 1956) which correlates temporal modulation of image intensities in two neighboring ommatidia. The detector model has two mirror-symmetrical subunits. In each subunit the signals of two input channels interact in a nonlinear way after the signals have been delayed by two lowpass filters with different time constants (τ1 = 1.5 steps and τ2 = 5.0 steps). In a next step the outputs of the two subunits are subtracted to obtain the direction of the motion stimulus. The motion detectors of flies show an asymmetric response. They respond stronger to a moving pattern in one direction than to the opposite direction, because the
time course of the two subunits is not completely mirror symmetric (Egelhaaf, Borst & Reichardt 1989). This is modeled by a gain of 1.0 for progressive and 0.7 for regressive motion.

Fig. 2. Motion response of the HSE (horizontal equatorial cell) at an elevation of $\theta = 0^\circ$. Normalized mean response to stimulation with progressive and regressive motion (redrawn from Hausen 1982).

Integration of the motion signals in the lobula plate: In the fly’s lobula plate neurons have been described which are specialized to certain motion patterns. For example the horizontal equatorial cells (HSE cells) respond maximal to horizontal progressive motion in the frontolateral field of view (Fig. 2). The receptive fields of the HSE cells of both hemispheres overlap in the frontal region and show a maximal sensitivity at about $-10^\circ$ to $60^\circ$ (Hausen 1982) in the equatorial part of the visual field. They respond stronger to progressive than to regressive image motion due to the asymmetric layout of the motion detectors. Modeling these HSE cells, two large field units integrate the motion information over a $196.5^\circ$ field of view in the right and left hemisphere respectively with an overlapping region of $33^\circ$ in the front. The sensitivity distribution $S(\varphi)$ is bilaterally symmetrical for the two integration units. Due to the asymmetric gain of the motion detectors, the large field units respond stronger to progressive than to regressive motion. The outputs $(\beta_l, \beta_r)$ of the integration units are coupled via transmission weights to the motor system.

The motor system: The agent is modeled as a simple kinematic system with two motors, ignoring its mass and inertia. In order to model the visuomotor control of flies this approximation can be made, because in flies the force of flight is almost completely used to overcome the air friction. After an initial acceleration due to the force produced by the wings, within a short time the fly reaches a constant velocity as the applied force is balanced by the increasing air friction. The velocity $v = (v_l, v_r)$ that results for the motors of the system is proportional to the force of the two motors. Each motor produces a constant basic force, causing a constant velocity $v_0$ which is modulated by the visual information, and the velocity of the two motors is

$$
v = v_0 - k \mathbf{W} \begin{pmatrix} \beta_l \\ \beta_r \end{pmatrix} = v_0 - k \begin{pmatrix} \omega_{ll} & \omega_{lr} \\ \omega_{rl} & \omega_{rr} \end{pmatrix} \begin{pmatrix} \beta_l \\ \beta_r \end{pmatrix},
$$

where the matrix $\mathbf{W}$ contains the transmission weights for the coupling of the outputs $\beta_l$ and $\beta_r$ of the two large field integration units to the left and right motors and $k$ is a constant factor. We assume bilateral symmetry for the sensorimotor coupling. The system has two degrees of freedom: translation in the
heading direction and rotation around the vertical body-axis. The distance between the two motors is \(1 \text{ u} \) given in units \(u\) of the agent’s size (\(1 \text{ u} = 1.4 \text{ m}\)). The basic velocity of the system is 0.14 \(u/\text{step}\), and the proportionality factor is \(k = 1.4 \text{ u/step}\).

3 The simulated environment

The simulated world is a quadratic arena with randomly distributed cubes of different sizes (Fig. 3). The texture that is mapped onto the walls of the arena and onto the cubes has an amplitude spectrum that falls off with \(1/\nu\) for the horizontal direction. Analysis of the amplitude spectrum \(A(\nu)\) (\(\nu = \text{spatial frequency}\)) of many natural scenes show that the amplitude falls off quickly by a factor of roughly \(1/\nu\) (Field 1987). Certainly there are also scenes that do not show this property like the night sky, grass, etc.. The large advantage of such a \(1/\nu\) characteristic is that the contrast energy is scale invariant over a large range. Therefore, the information provided by the sensors will be roughly independent from the distance to the textured objects.

![Fig. 3. 360° view of agent in a simulated environment with randomly distributed cubes.](image)

4 Genetic algorithm

**Parameter optimization:** The parameters that describe the shape of the sensitivity distribution and the transmission weights that couple the output of those units to the motor system are optimized with GAs. The design of the GA is the same as in previous work (Huber, Mallot & Bühlhoff 1996). The sensitivity distribution is coded by 8 function values \(S(\varphi_j)\) with \((j = 1, ..., 6)\) and \(\varphi_j = 177.7^\circ, 150.1^\circ, 122.5^\circ, 94.9^\circ, 66.3^\circ, 38.7^\circ, 11.1^\circ, -16.5^\circ\). The other function values \(\varphi \in [-16.5^\circ, 180^\circ]\) are computed by cubic spline interpolation. The GA optimizes 10 real value parameters, 8 for the sensitivity distribution and 2 for the bilateral symmetric transmission weights. A population size of 50 individuals is used. The crossover rate is \(p_c = 0.2\), the mutation rate \(p_m = 0.4\) and the scaling factor \(n_c = 2.0\).

**Fitness function:** The fitness is a piecewise summation of the distance the agent covers in 50 steps:

\[
    f_5 = \sum_{t_s} \sqrt{(x_{t_s} - x_{t_{s-1}})^2 + (y_{t_s} - y_{t_{s-1}})^2},
\]  

(2)
with $t_s = 50s$ and $s = 1, 2, \ldots, m$. In addition agents which move backwards ($v_i < 0$) receive a zero fitness. The maximum number of time steps $t_m$, the agent moves through the environment increases every generation $i$: $\Delta t_m(i) = 50$ steps. At generation 1, $t_m(1) = 500$ steps and $m = 10$. Such a floating number of steps increases the difficulty of the task every generation.

5 Results

At generation 25 an agent evolves with a sensitivity function (Fig. 4) that has a maximum at $\pm 11^\circ$ and a sensitivity larger than 0.6 between $\pm 5^\circ$ and $\pm 20^\circ$ for the large field integration unit on the right and left hemispheres, respectively. Although there is a local minimum at $\pm 40^\circ$ the overall sensitivity is large in the frontal and frontolateral visual field. Motion in the back part of the visual field is weaker and inhibits the integration units. The transmission weights $\omega_{rf} = \omega_{fr} = -0.0298$ that couple the contralateral outputs of the large field units with the motors are slightly weaker than the ipsilateral weights $\omega_{ll} = \omega_{rl} = -0.0527$. As a consequence, a large image motion in the frontal visual field excites the ipsilateral motor stronger than the contralateral. Thus the agent turns away from obstacles in the frontolateral visual field and is able to avoid the obstacles for more than 4000 time steps. If the agent turns away from an obstacle in the frontal part of the visual field, it may appear in the back part of the visual field. The resulting optical flow inhibits the output signals of the integration unit, and the agent executes a small turning response in the opposite direction. This is of advantage because an inverted turning response stabilizes the agent again on a new course. A turning response in the same direction would cause further rotations in front of the obstacle.
6 Discussion

We presented agents that use visual motion information to avoid the obstacles in computer-simulated environments. The agent does not need to execute pure translations or have knowledge about its own velocity in order to avoid obstacles successfully. We applied genetic algorithms to optimize the sensitivity distribution of the large field integration units. The sensitivity distribution determines which parts of the 360° horizontal motion field are essential for the obstacle avoidance behavior. For the frontal and frontolateral region of the receptive field results a sensitivity distribution comparable to that described for the HSE cells of flies. The evaluation of image motion in these regions is important for a successful obstacle avoidance behavior. Cells with the same overall sensitivity distribution with inhibitory regions in the back and excitatory regions in the front have not been found in biological systems; however, the superposition of several cells might have a similar effect on the fly’s turning response. The evolution runs for 25 generations only, due to computation times. A larger number of generations as well as the additional constraint of purely excitatory integration units probably can further increase the similarity between the sensitivity distribution of HSE cells and the integration units of the agent.

References