From Flying Bees to Autonomous Robots

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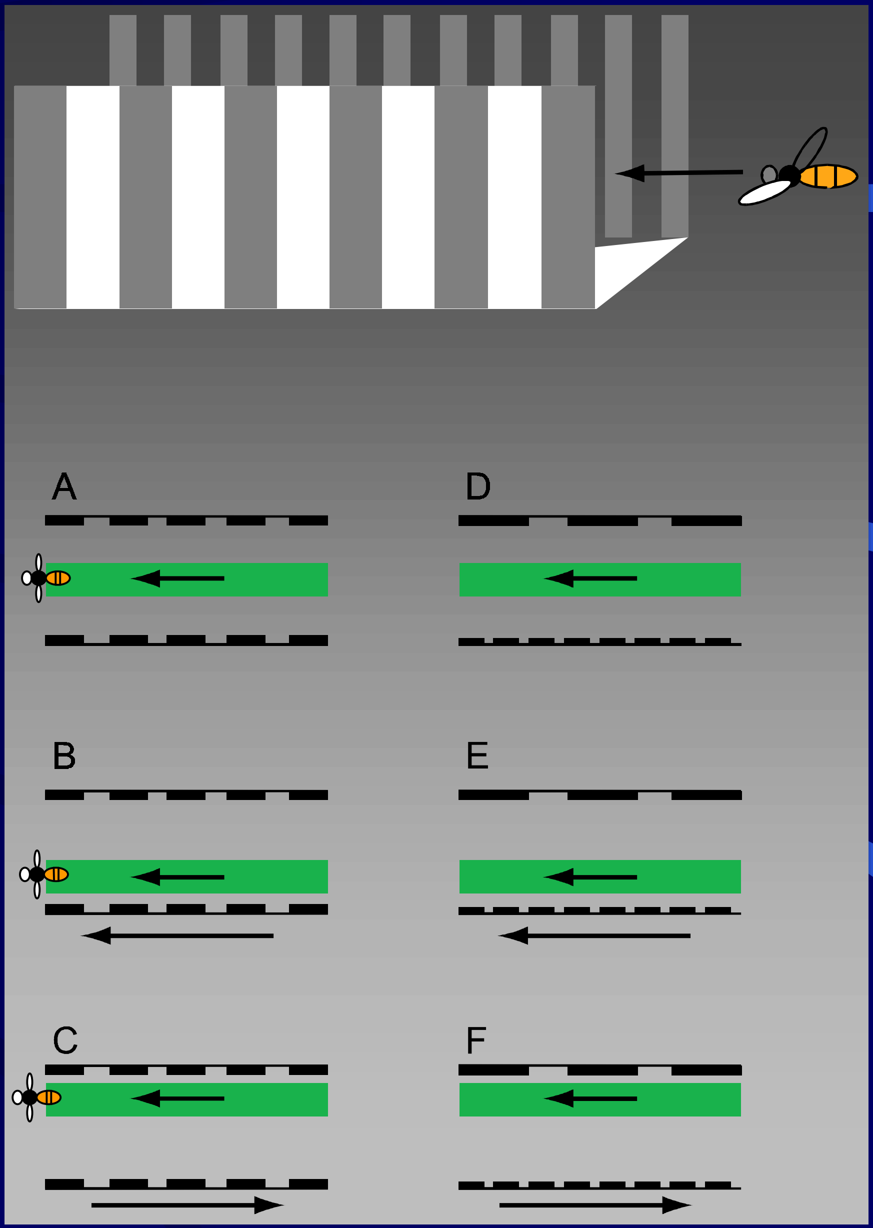
Peculiarities of insect vision

Small interocular separation

Therefore, stereo vision is difficult

Insects rely heavily on image motion cues to infer object distance, perceive the world in 3-D and navigate in it

Bees negotiate narrow gaps by balancing the image velocities in the two eyes

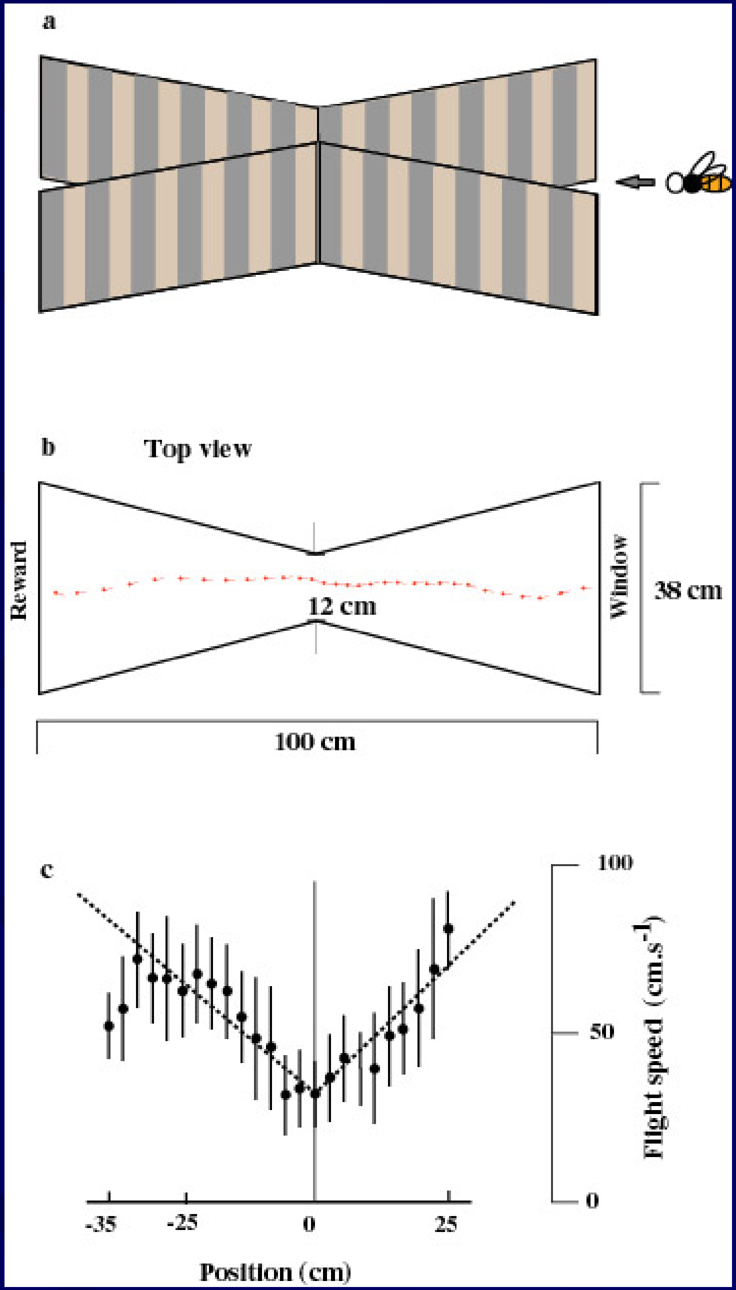


Kirchner & Srinivasan
Naturwissenschaften (1988)

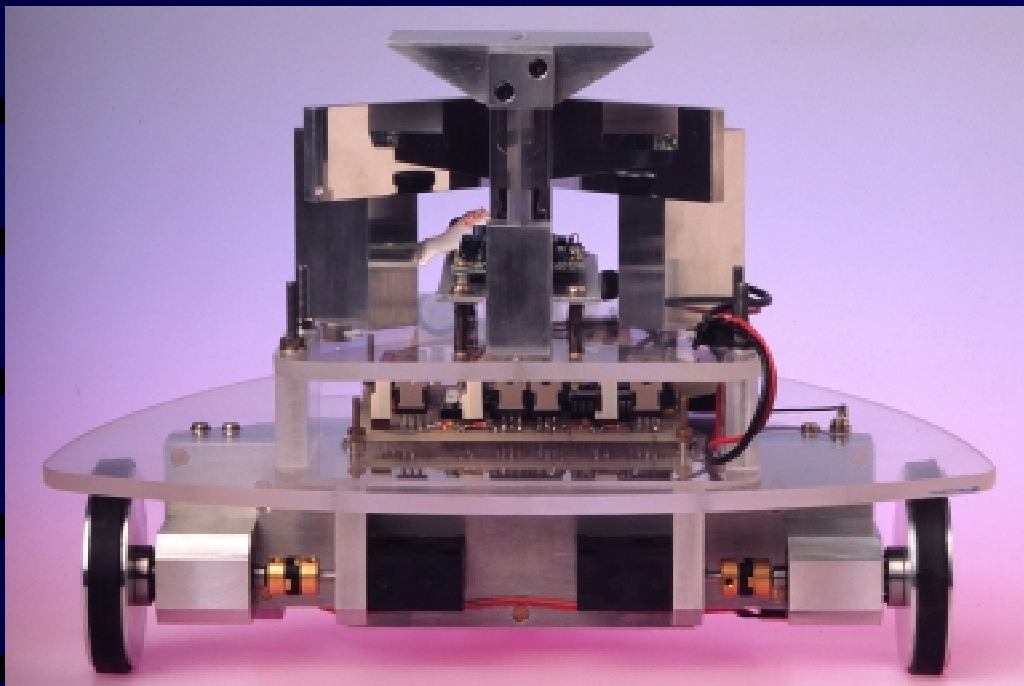
Srinivasan, Lehrer, Kirchner & Zhang
Vis. Neurosci. (1991)

Control of flight speed

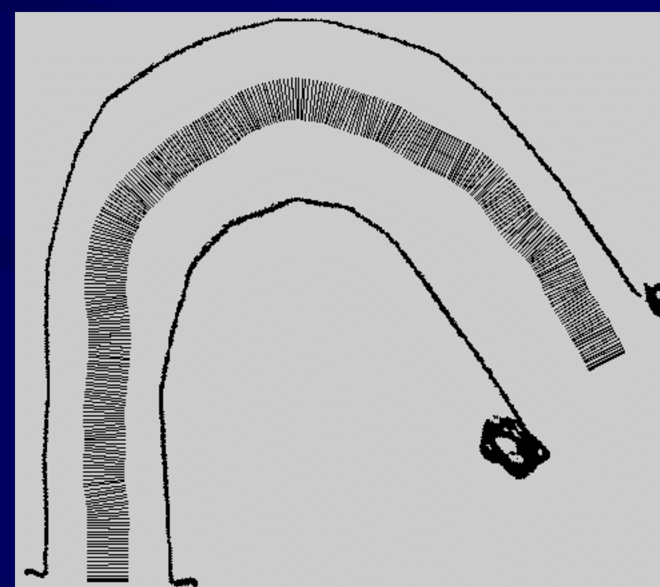
Speed of flight is regulated by holding the global image velocity constant



Srinivasan, Zhang, Lehrer & Collett
J. Exp. Biol. (1996)



This robot, about the size of a skateboard, navigates along corridors by balancing optic flows on the left and the right

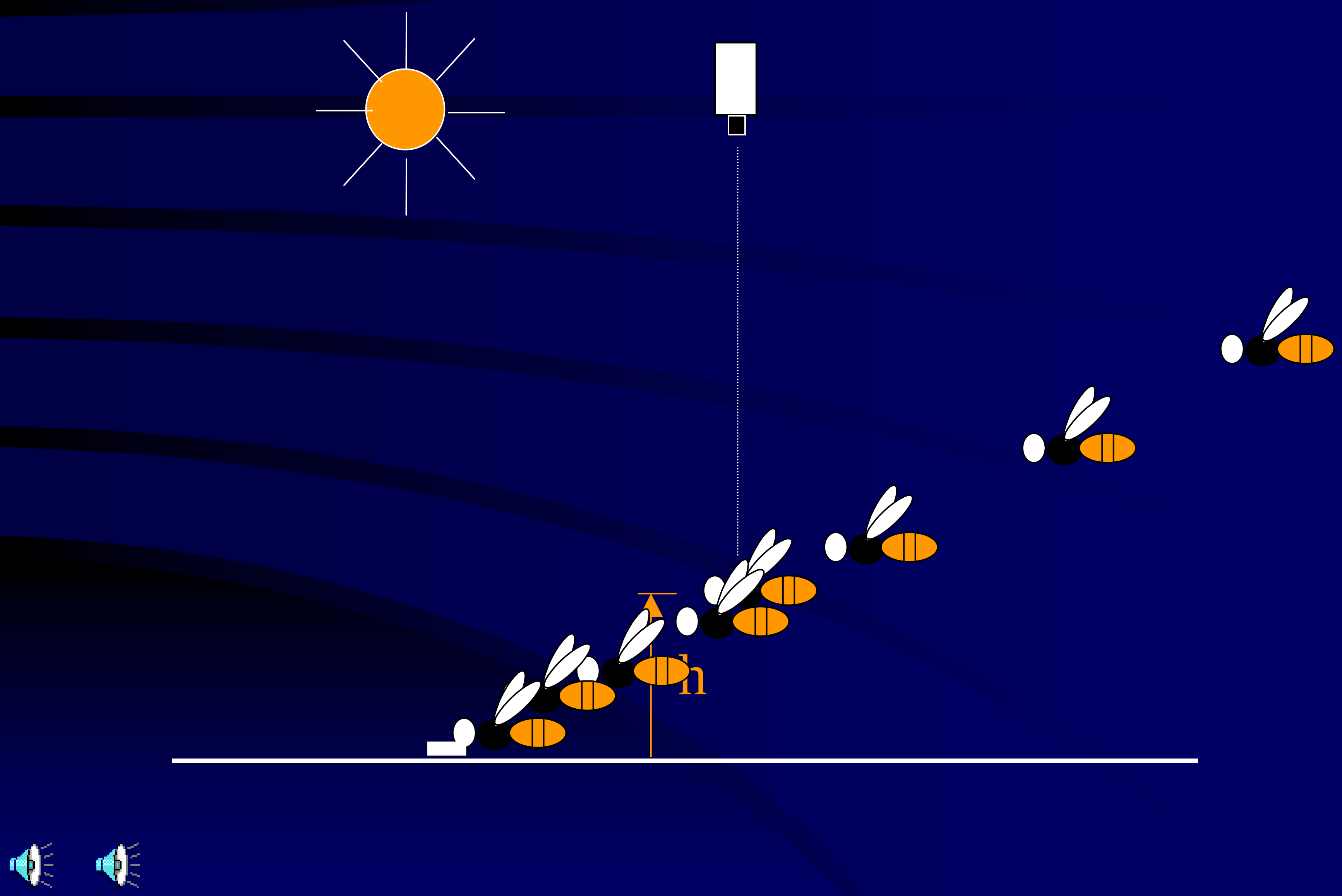


Weber, Chahl, Srinivasan & Venkatesh (1997)

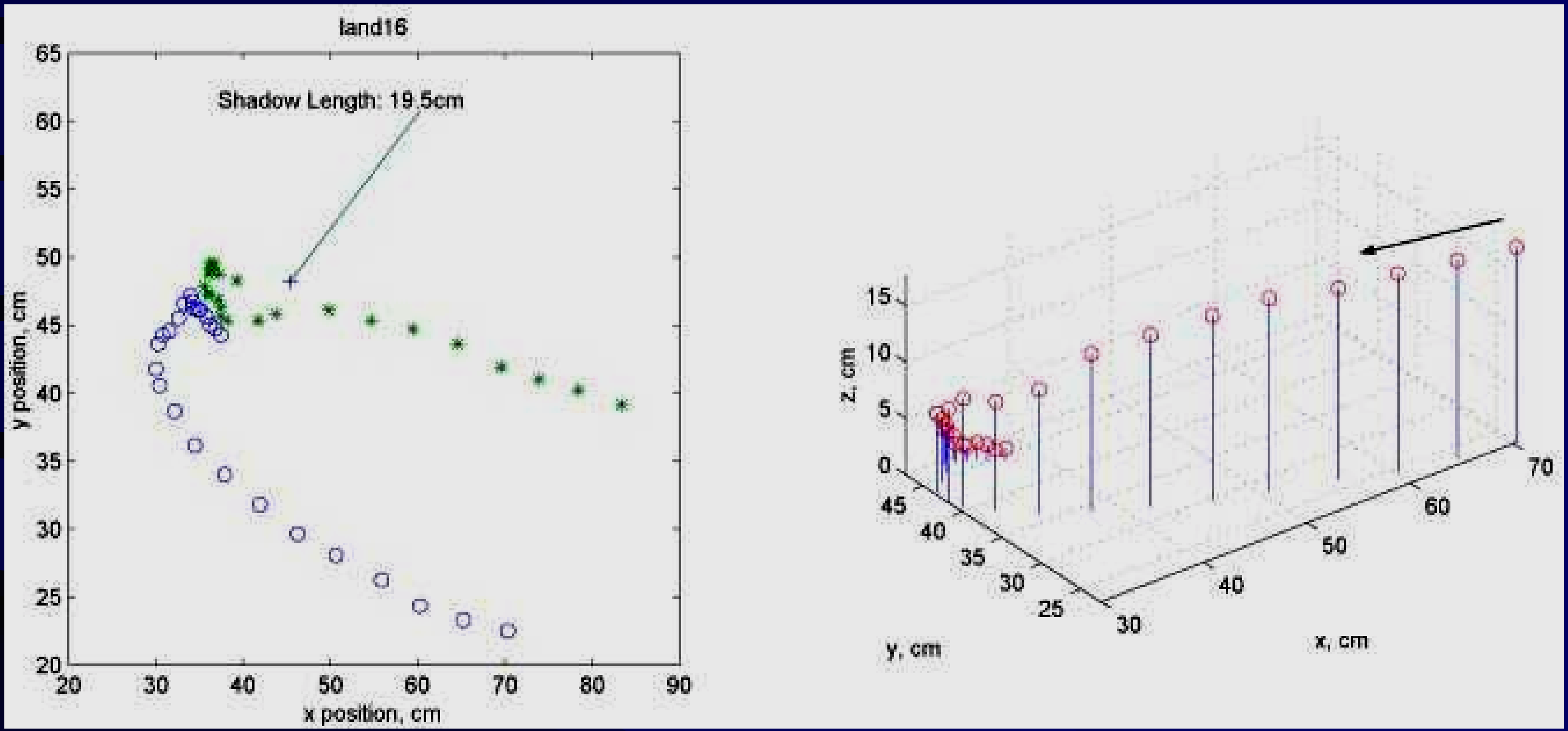
Landing

How does a bee perform a smooth, grazing landing on a horizontal surface ?

Filming trajectories of landing bees

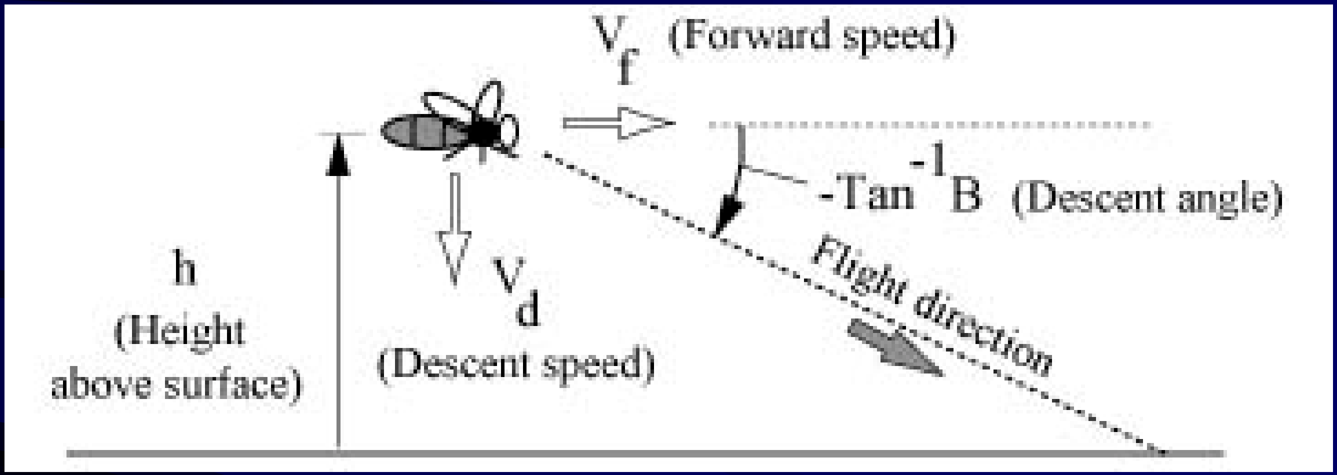


Reconstruction of landing trajectories in 3d

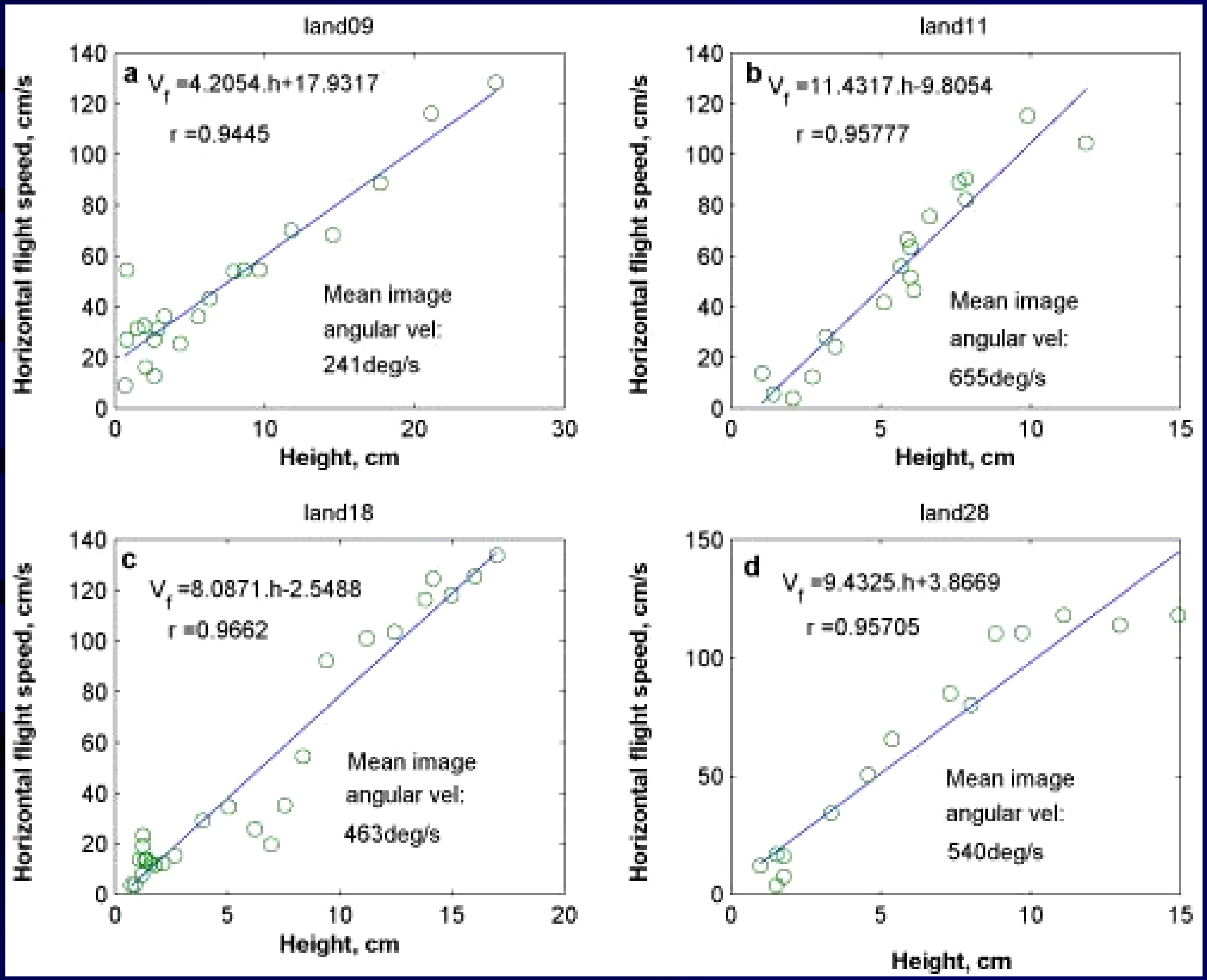


Srinivasan, Zhang, Chahl, Barth & Venkatesh
Biol. Cybern. (2000)

Landing parameters



Horizontal flight speed versus height



Srinivasan, Zhang, Chahl, Barth & Venkatesh, *Biol. Cybern* (2000)

Rules for landing

1. Ground image speed is held constant

$$V_f(t) = \omega.h(t)$$

2. Instantaneous descent speed $V_d(t)$ is coupled to instantaneous forward flight speed $V_f(t)$:

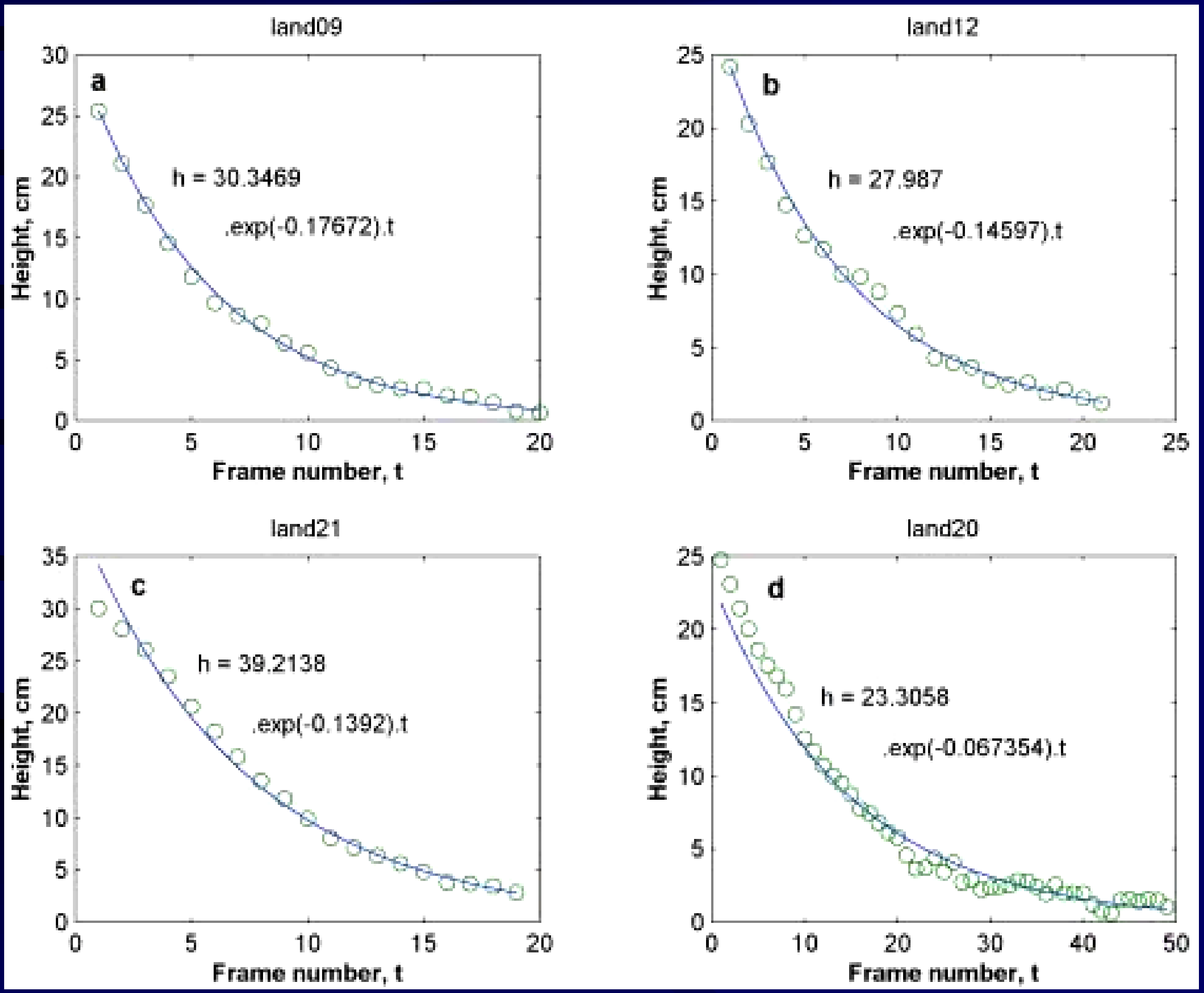
$$V_d(t) = -\frac{dh(t)}{dt} = B.V_f(t)$$

Model prediction 1:

$$h(t) = h(t_0).e^{-\omega.B.t}$$

$\Rightarrow$ Height decreases exponentially with time

Test of prediction 1



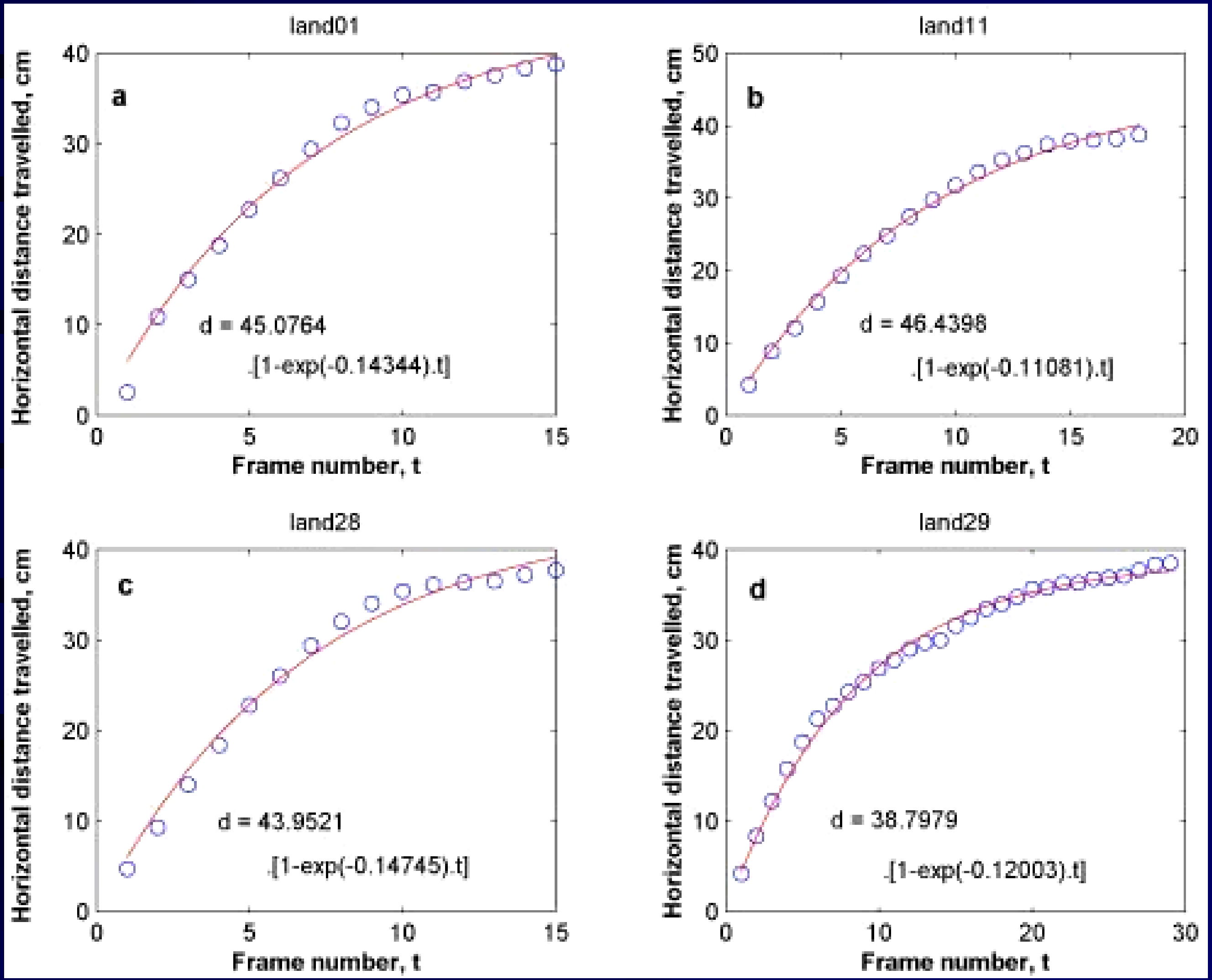
Srinivasan, Zhang, Chahl, Barth & Venkatesh, *Biol. Cybern* (2000)

Model prediction 2:

$$Hordist = \frac{h(t_0)}{B}.\left[1 - e^{-\omega .B.t}\right]$$

⇒ Cumulative horizontal distance travelled is a saturating exponential function of time

Test of Prediction 2



Srinivasan, Zhang, Chahl, Barth & Venkatesh, *Biol. Cybern* (2000)

Test of landing algorithm on a gantry robot

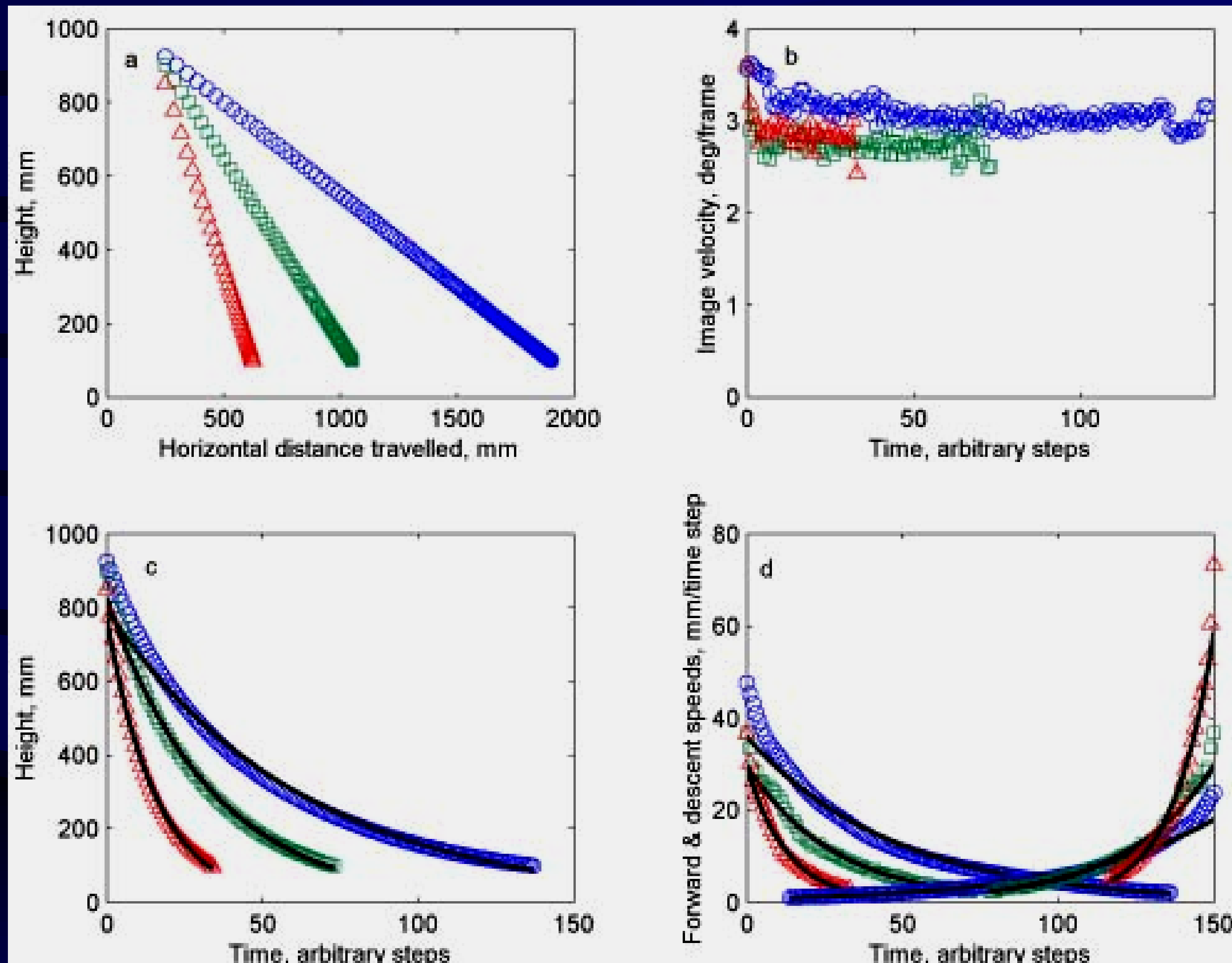
Computer-controlled gantry with panoramic vision head

Panoramic image

X flow

Y flow

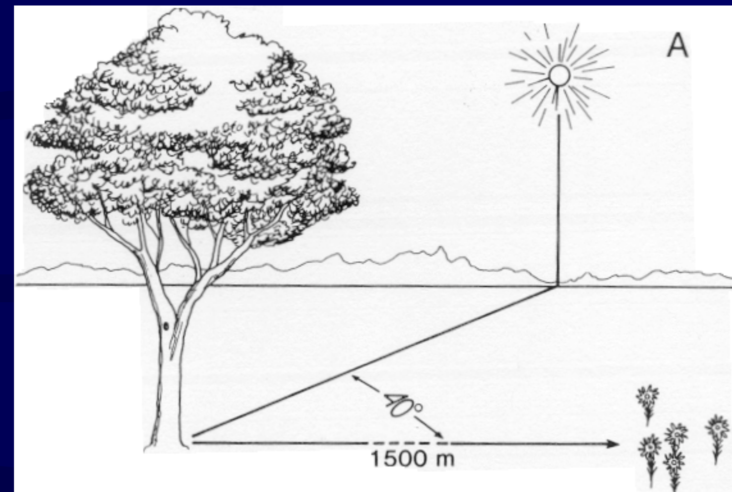
Gantry experiments: results

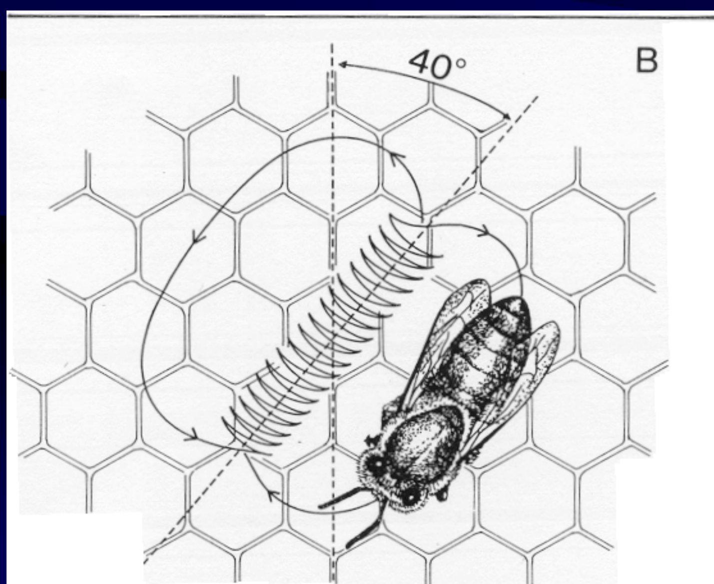


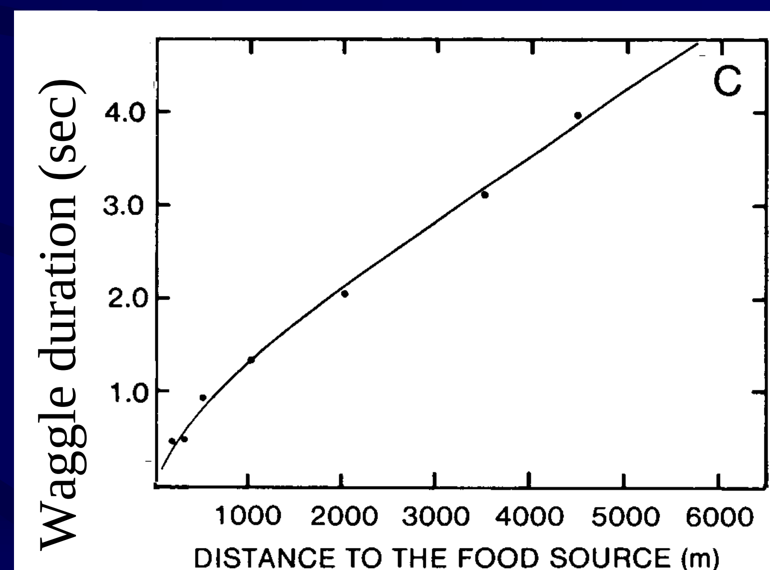
Srinivasan, Zhang, Chahl, Barth & Venkatesh, *Biol. Cybern.* (2000)

Honeybee odometry

The waggle dance





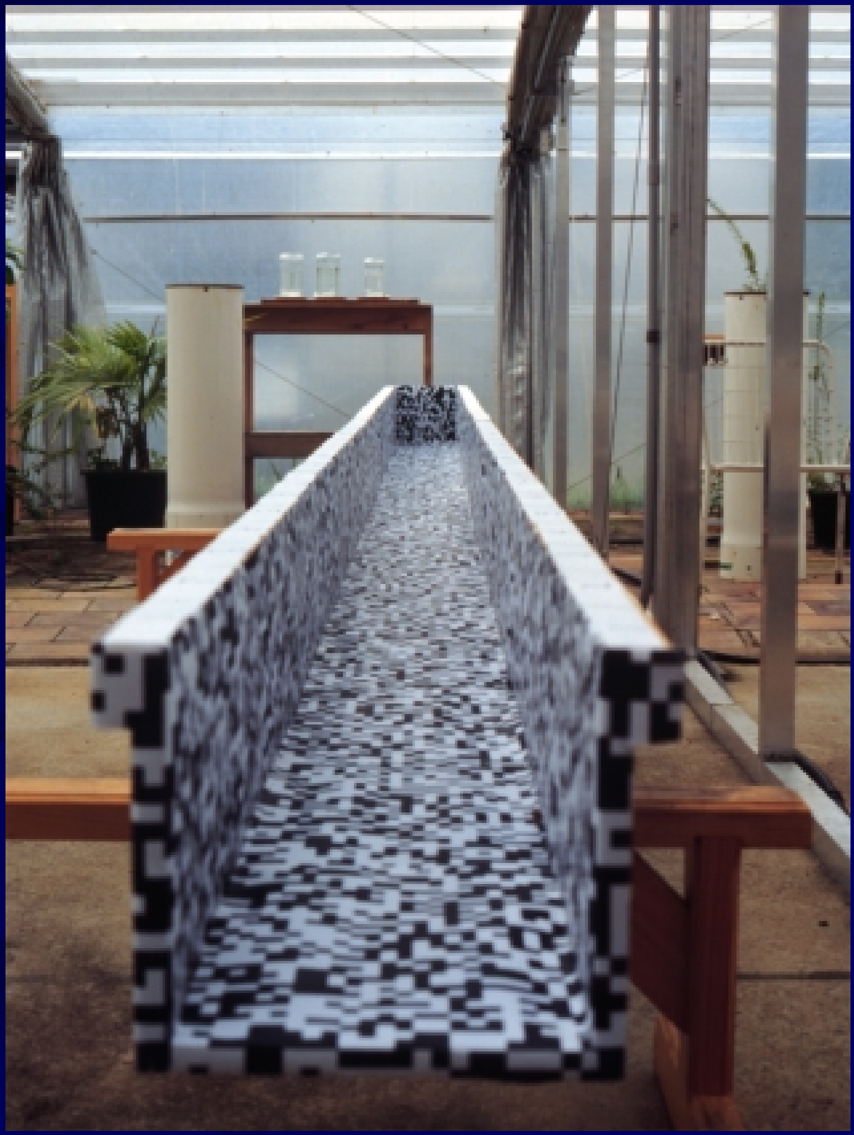


Q: How does a bee work out how far she has flown?

AWBFF: All-Weather Bee Flight Facility

Honeybee odometry

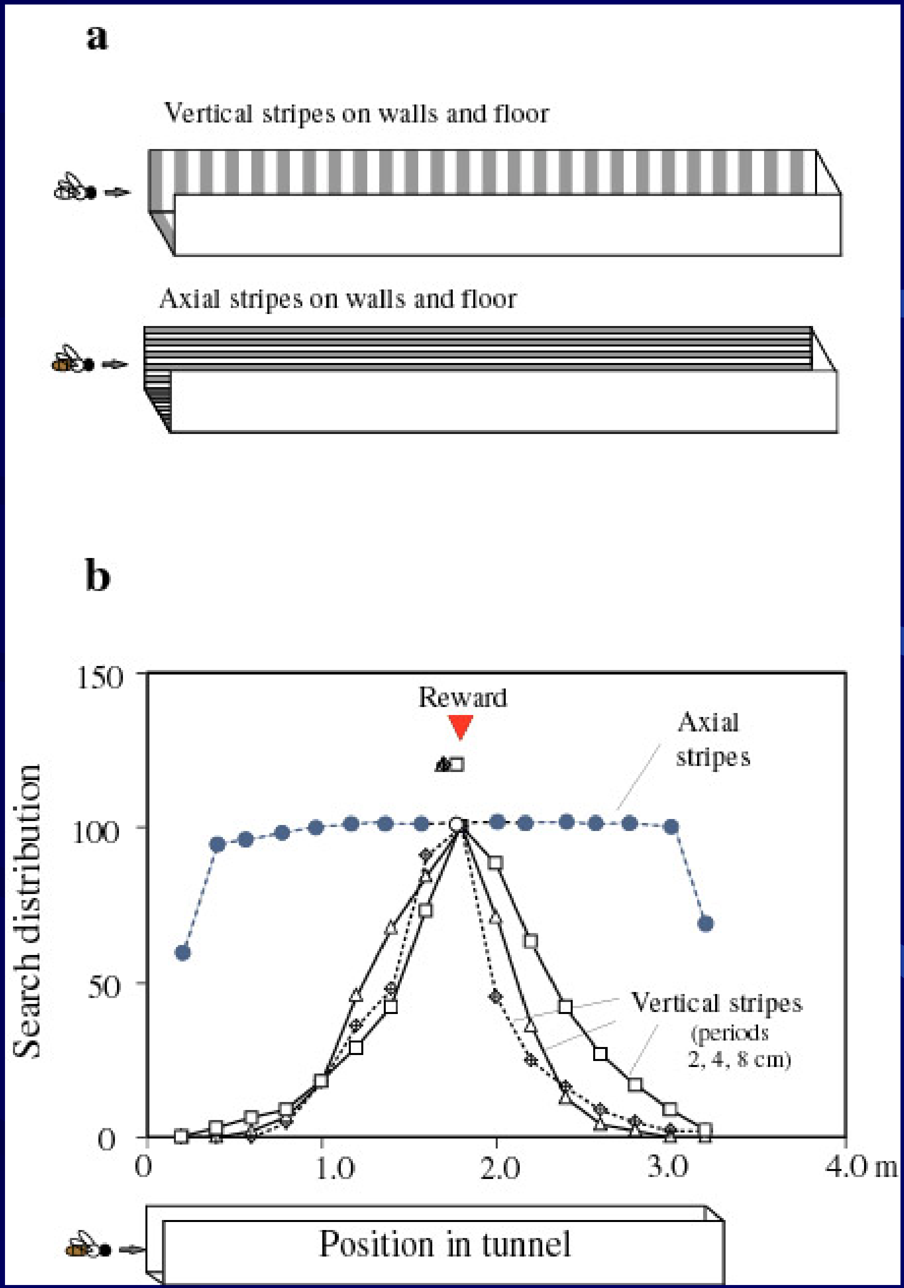
Bees are trained to find a food source placed at a fixed location inside a tunnel lined with a visual texture

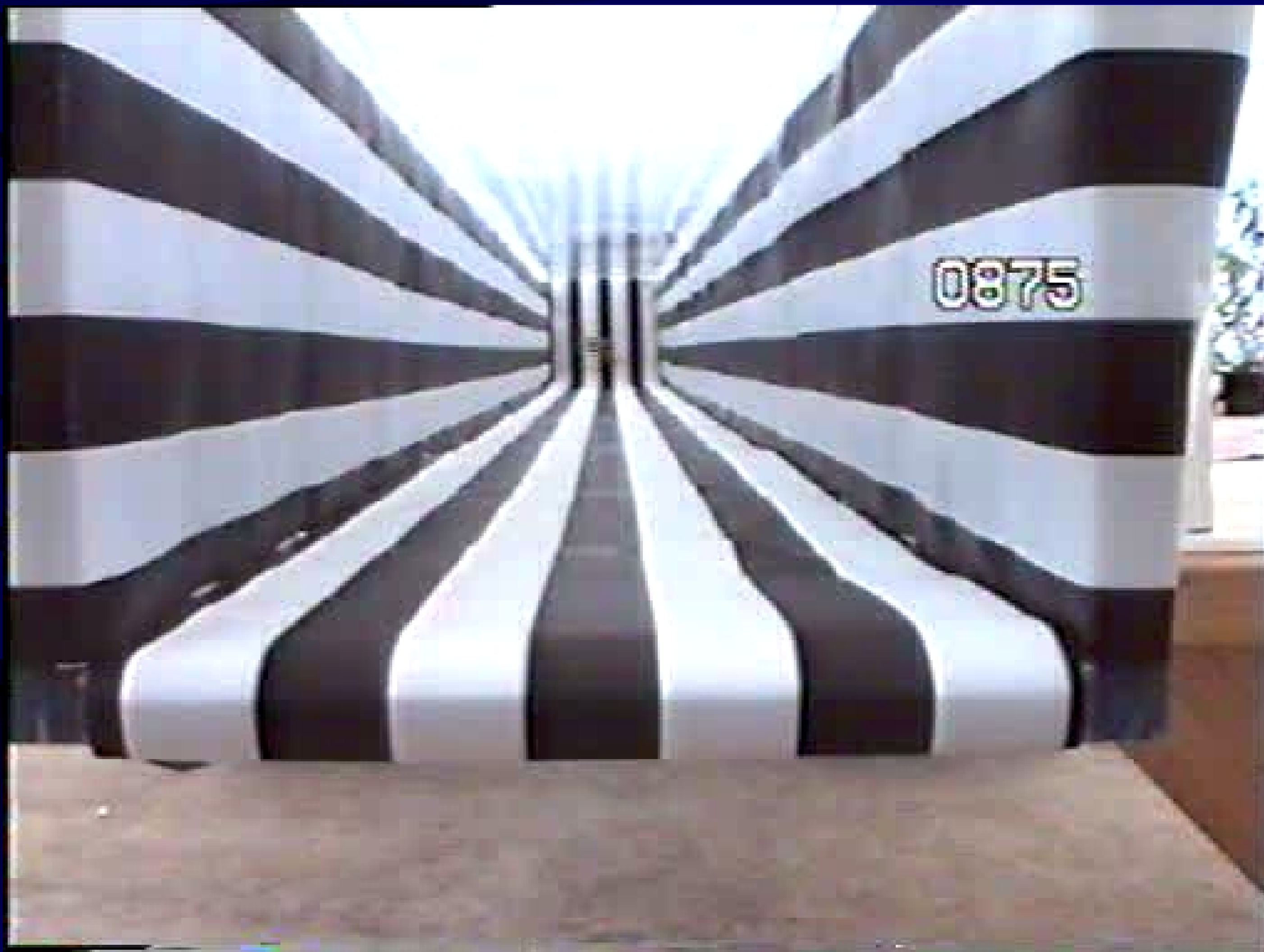


Honeybee odometry

Bees can learn the location of a food source placed inside a tunnel lined with vertical stripes

They *cannot* learn the location if the tunnel is lined with horizontal stripes

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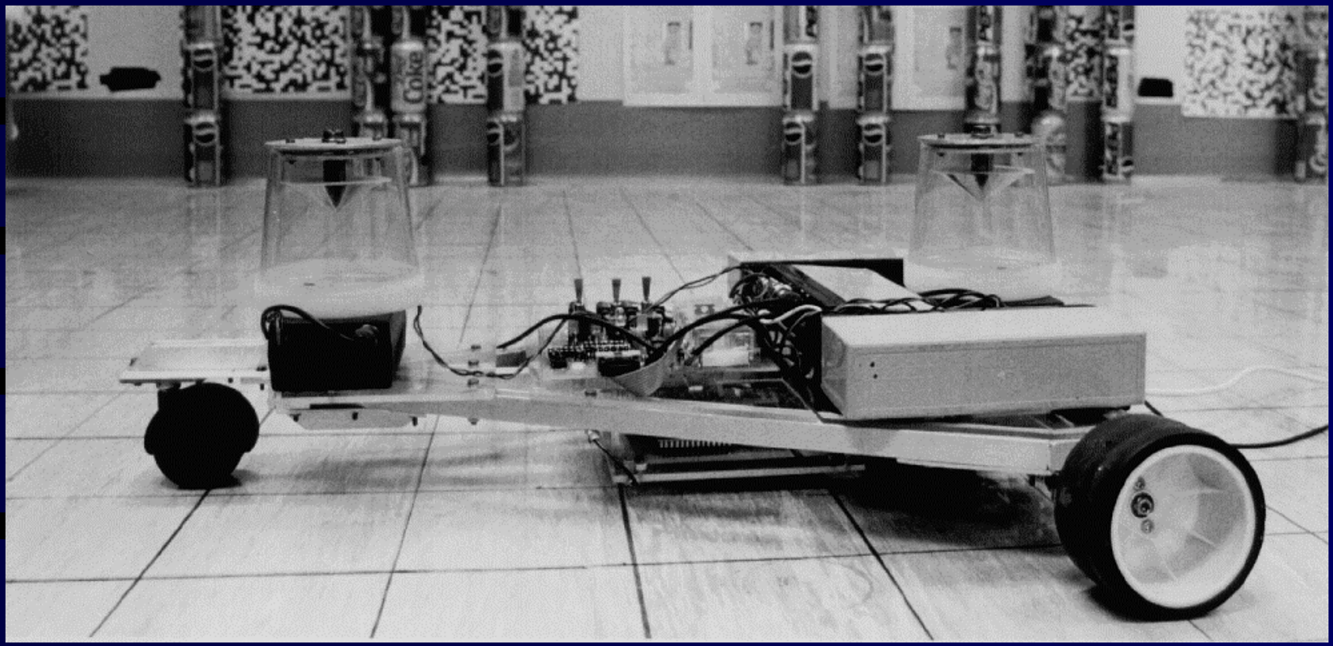
Honeybee navigation: What is the nature of the odometer?

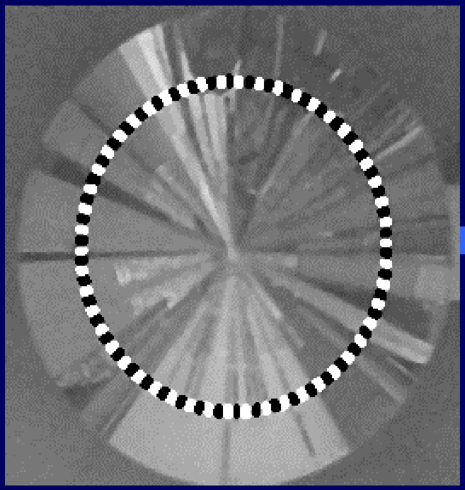
Landmark count
Time of flight
Wingbeat count
Energy consumption

Airspeed integration
Inertial navigation

Integration of optic flow

Egomotion computing robot

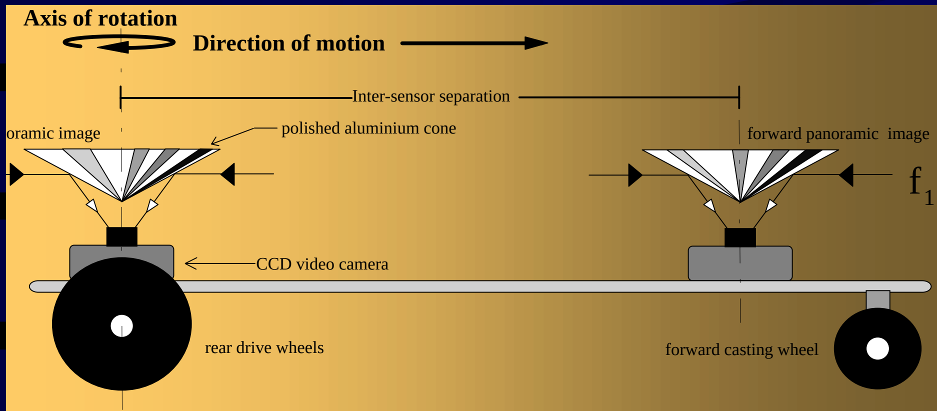




This robot, about the size of a skateboard, estimates its motion through the environment by integrating optic flow (or, more accurately, image deformation)

It requires no prior knowledge of the environment

Chahl & Srinivasan, *Biol. Cybernetics* (1996)



$$\hat{f}(\theta) \cong (1-\alpha) f_0(\theta) + \alpha f_1(\theta) \qquad (1)$$

We minimise the mean square error between f(θ) and $\hat{f}(\theta)$. That is, we minimise

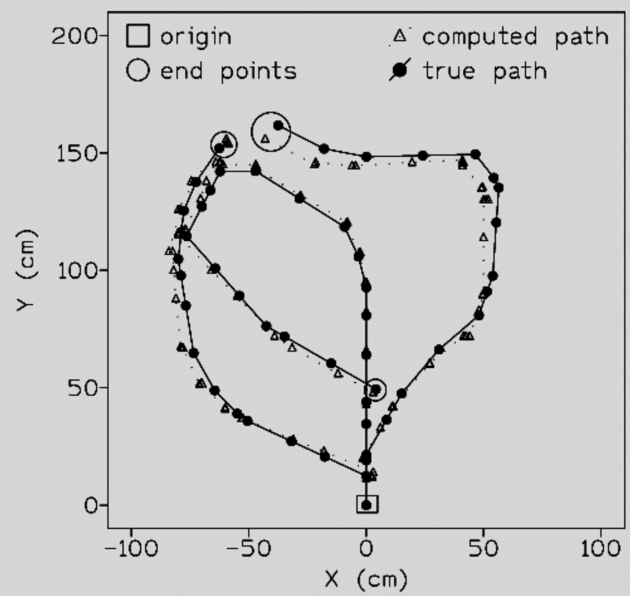
$$\int_0^{2\pi} \left[\{(1-\alpha) f_0(\theta) + \alpha f_1(\theta)\} - f(\theta)\right]^2 d\theta \qquad (2)$$

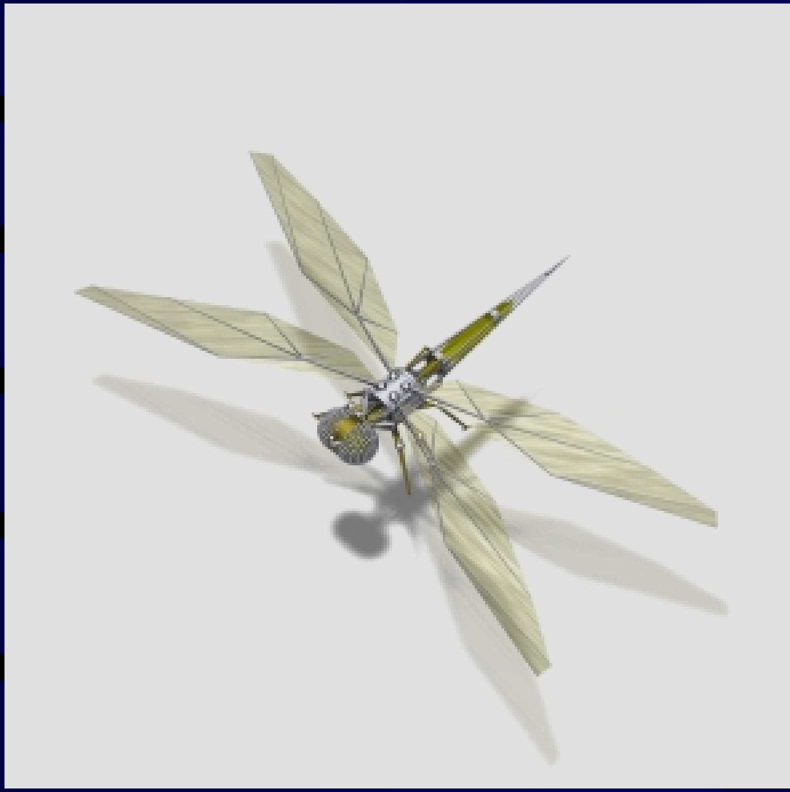
with respect to **α.**

This minimisation yields

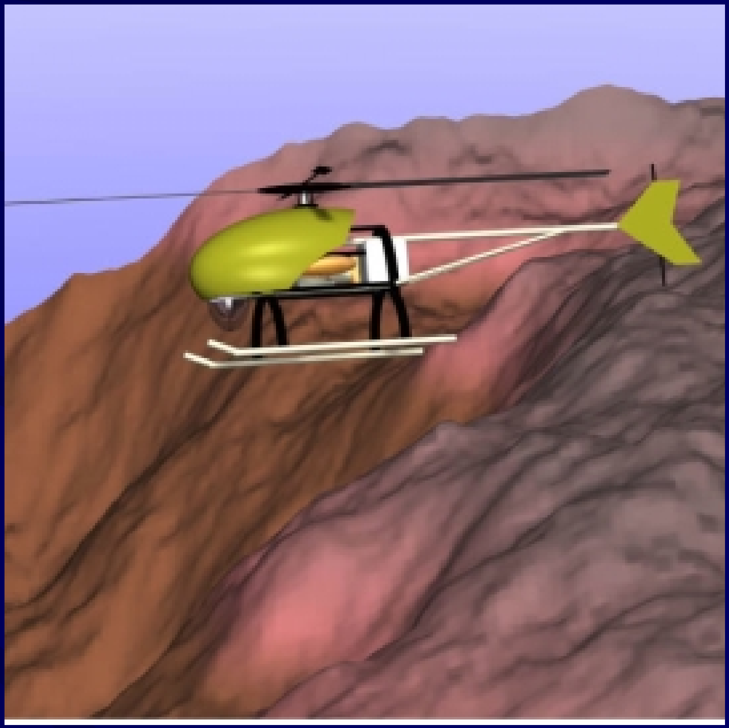
$$\alpha = \frac{\int_0^{2\pi} \left[f(\theta) - f_0(\theta)\right]\left[f_1(\theta) - f_0(\theta)\right] d\theta}{\int_0^{2\pi} \left[f_0(\theta) - f_1(\theta)\right]^2 d\theta} \qquad (3)$$

Since $f_0(\theta)$, $f(\theta)$ and $f_1(\theta)$ are known, **α** is readily computed.

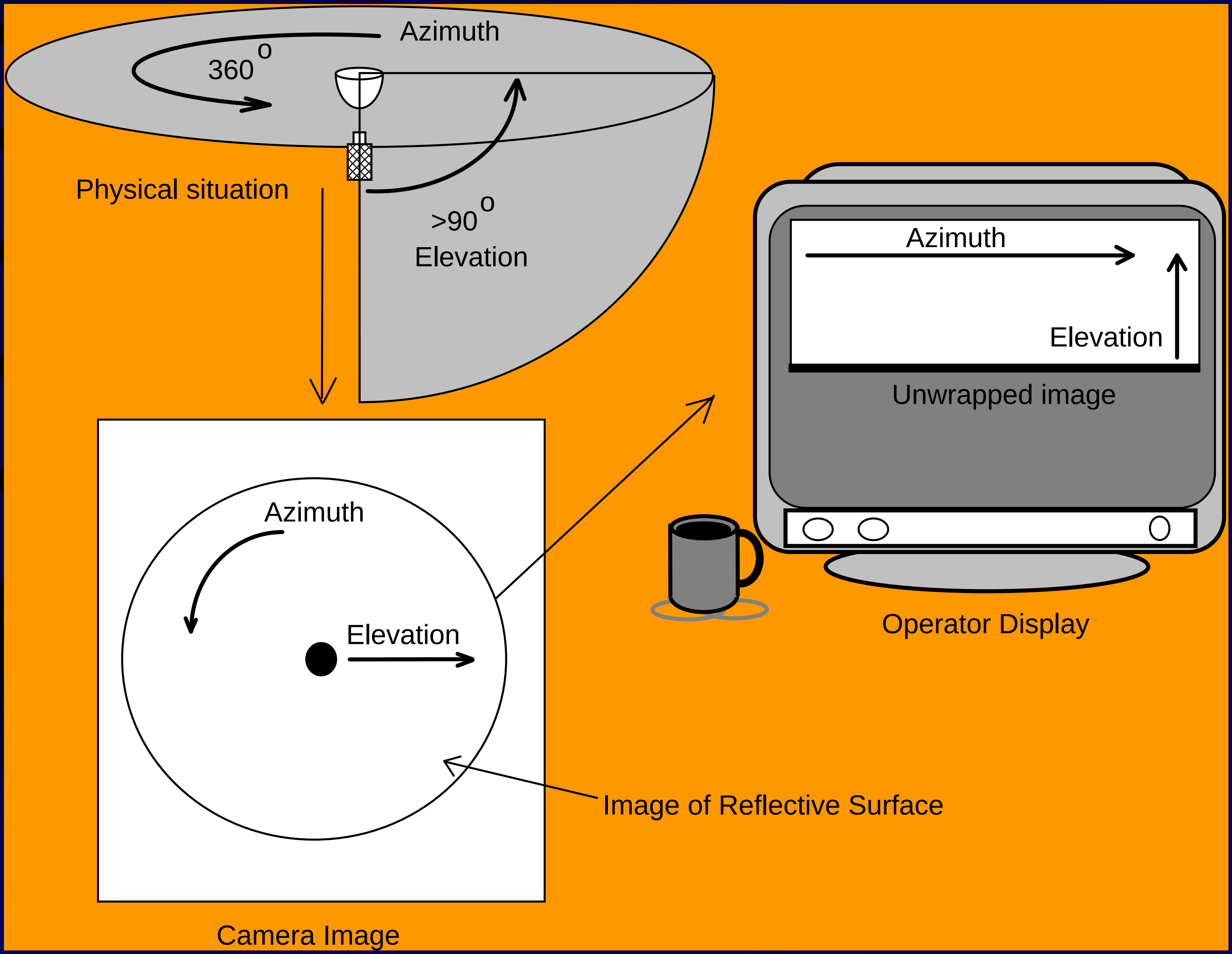




Flying machines



Panoramic Imaging System



The system comprises a standard video camera viewing a specially shaped reflective surface. The surface has the property that a given change in the angular elevation of view in the external environment maps to a constant radial displacement in the camera's image

Constraint equation for generating profile of panoramic imaging surface

Chahl & Srinivasan, *J. Opt. Soc. Am. A* (1997)

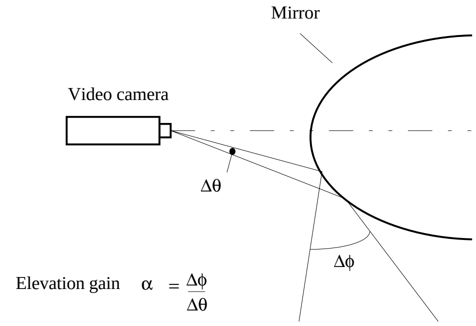


Figure 1
Camera-mirror configuration, illustrating the elevation gain α .

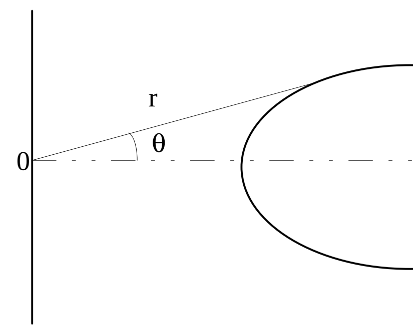


Figure 2
Polar co-ordinate system for definition of mirror profile .

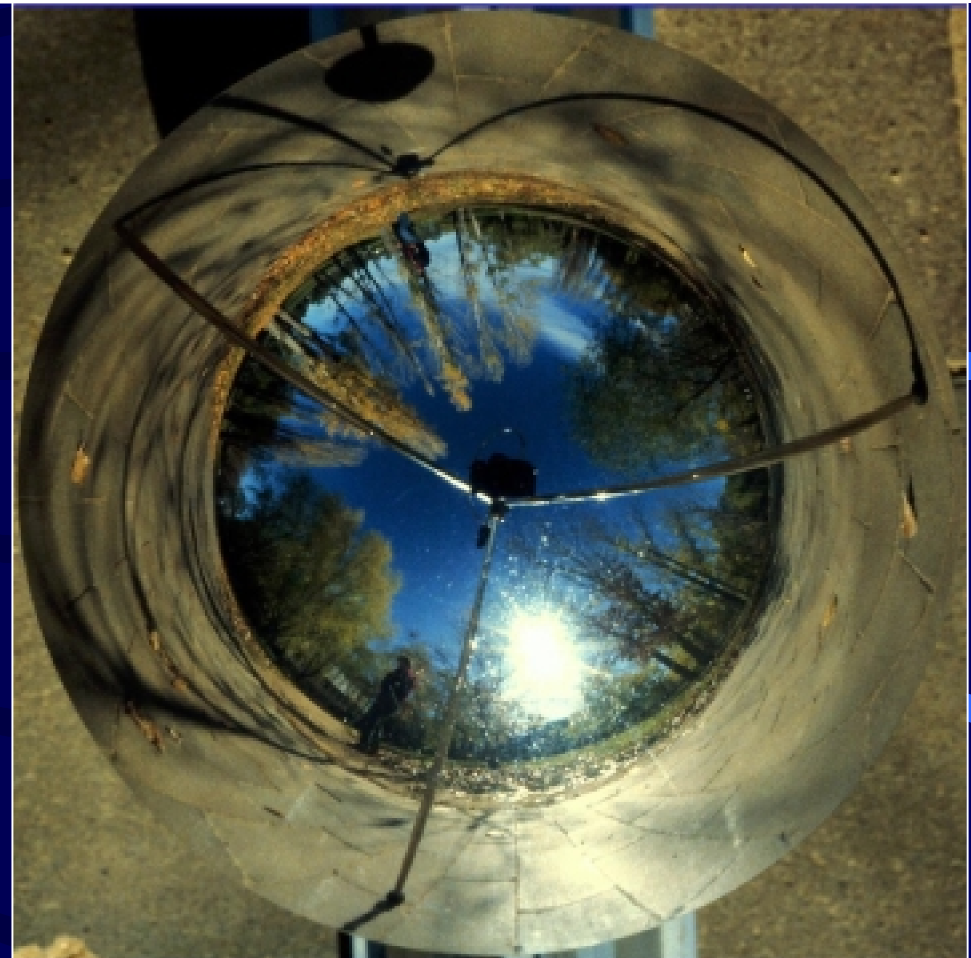
Generating equation:

$$\frac{d}{d\theta}\left[\tan^{-1}\left(r\frac{d\theta}{dr}\right)\right] = \kappa, \qquad \text{where } \kappa = -(1+\alpha)/2$$

$$\Rightarrow \sin[A - \theta(1+\alpha)/2] = (Br)^{(1-\alpha)/2}$$

Constants of integration A and B are set by boundary conditions: distance and slope of surface at θ = 0.

Image acquired by camera



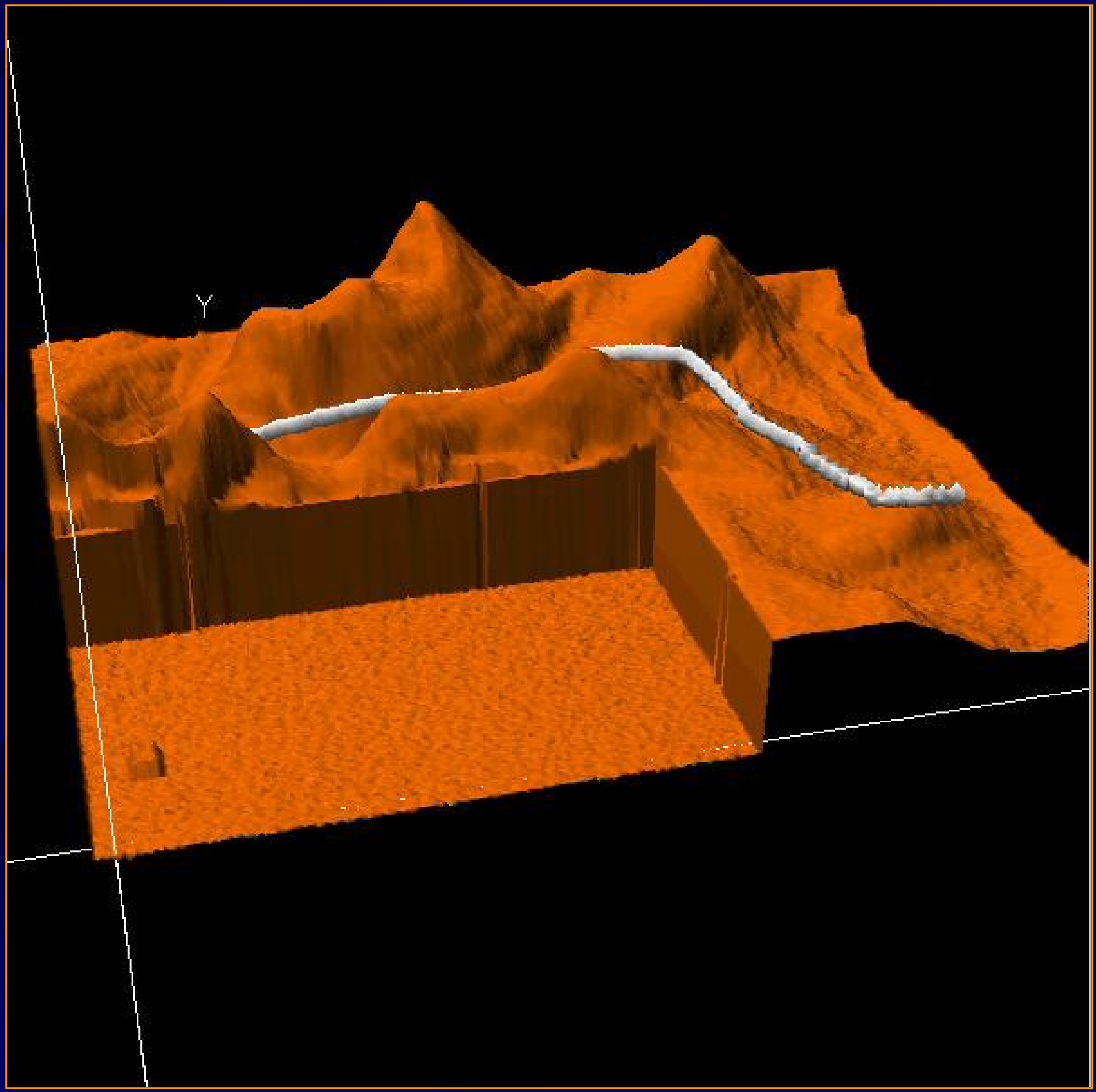
Digitally unwarped panoramic image

Navigation in 3-D

Gantry -based, insect-inspired navigation system emulates flight in realistic terrain

Navigation in 3-D(contd.)

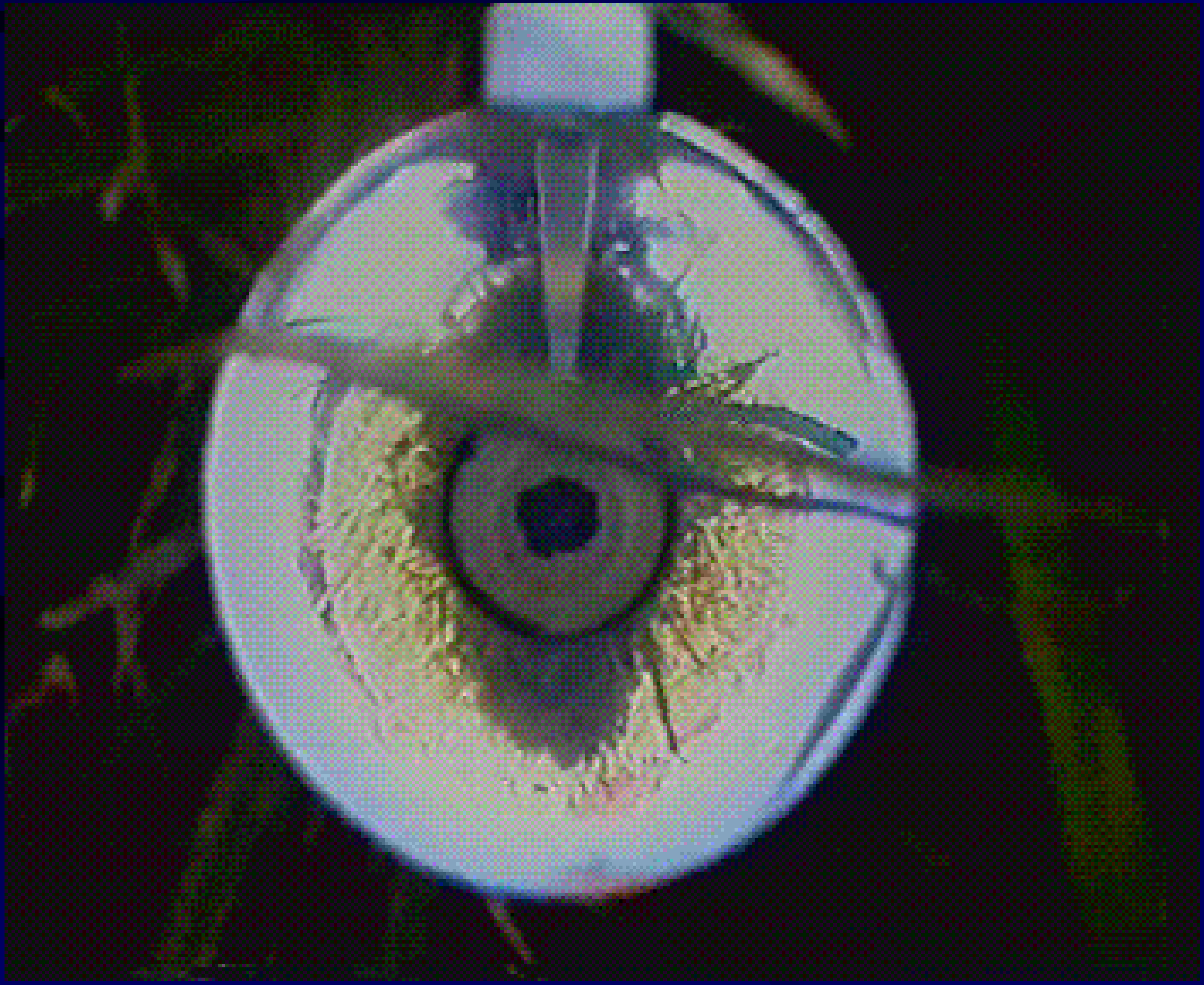
Development and testing of algorithms for landing, terrain following, gorge following, obstacle avoidance and point-to-point navigation



Chahl & Srinivasan (2000b)


Commands
Alt
50
200
700
Start

Panoramic video imaging from a helicopter



Summary

1. Principles of insect vision and navigation

2. Applications to robotics

Colleagues and collaborators

1. Insect vision

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Wolfgang Kirchner	University of Konstanz
Miriam Lehrer	University of Zürich
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Jürgen Tautz	University of Würzburg
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Colleagues and collaborators

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Peter Sobey	Australian National University
Gert Stange	Australian National University
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Keven Weber	Curtin University
Dale Wilson	Oxford University


Shaowu Zhang


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