Video Data and the Inverse Perception Problem in Animal Flight Behaviors

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10-th Summer School on Geometry, Mechanics and Control June, 2016

Overview of Four Lectures

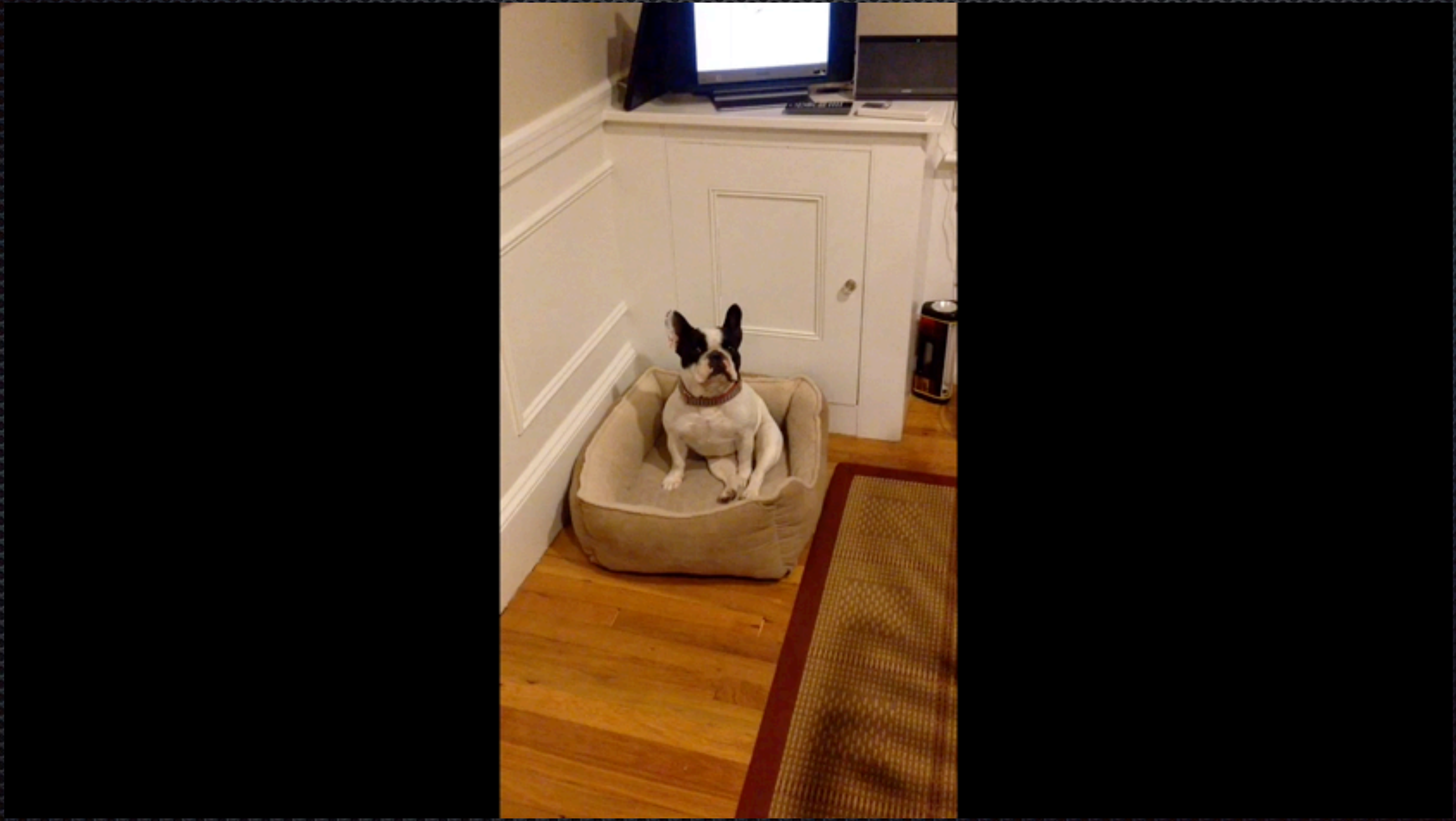
- Lecture 1: Video Data and the Inverse Perception Problem in Animal Flight Behaviors
- Lecture 2: Bio-Inspired Flight Control — What we learn from birds and bats
- Lecture 3: Topological Data Analytics
- Lecture 4: Topological Aspects of Optimal Information Acquisition

Theme of the Four Lectures

- Field studies of bats — what we did; why we did it
- Navigation laws used by flying animals
- Perception
- Topological Data Analytics
- Geometric and topological aspects of optimal information acquisition

Perception is species specific

Cassidy — what is she thinking?



Perception is species specific — Nicolaus Troje

Perception is species specific

Nicolaus Troje's home page:

http://www.biomotionlab.ca/niko.php

The Inverse Perception Problem in Animal Flight Behaviors

Talk Outline

1. What is perception-enabled control and why is it different?
2. Control in the natural world is perception enabled - how perceptions differ from one species to the next.
3. How animals react to optically sensed features.
4. Introduction to *tau* and *looming.*
5. Tau as a control signal.
6. Some biologically plausible control laws.
7. Profound open challenges.

Motion control based on perception

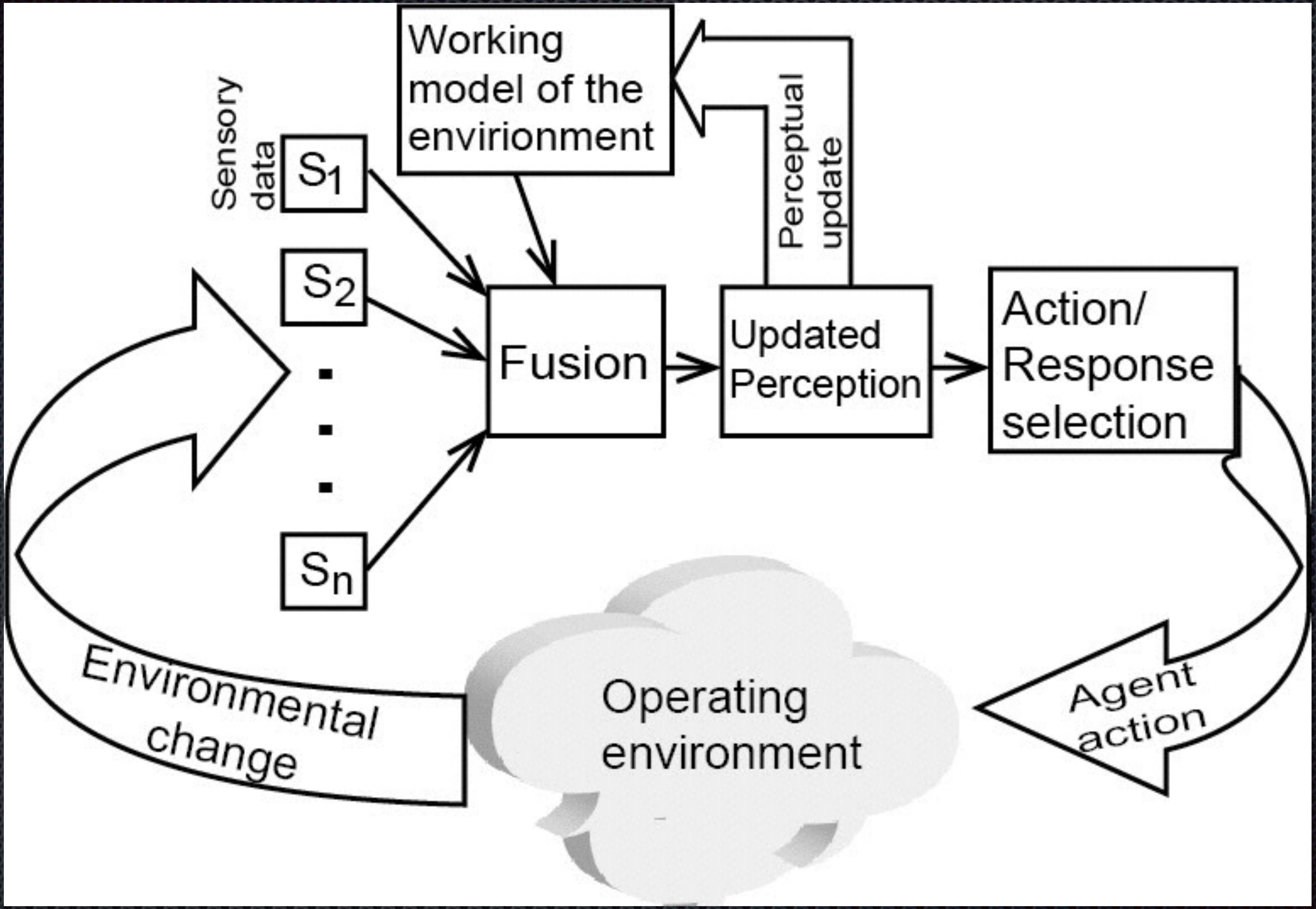
How do they do it?

The great challenge of the "*inverse perception problem*"

There is an important contrast: "uphill analysis and downhill invention." It is easy to invent machines to possess certain behavioral characteristics. It is quite easy to observe the full repertoire of behavior of these machines - even if it goes beyond what we had originally planned, as it often does. But it is much more difficult to start from the outside and to try to guess internal structure just from the observation of behavior."

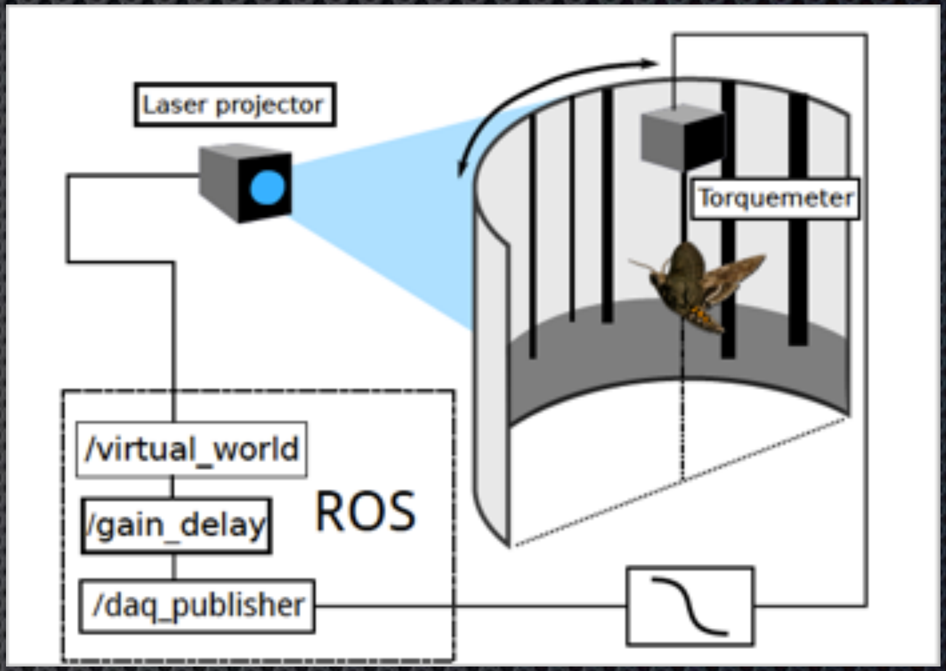
---Valentino Braitenberg, *Vehicles*, 1984

The perceptual basis of motion control

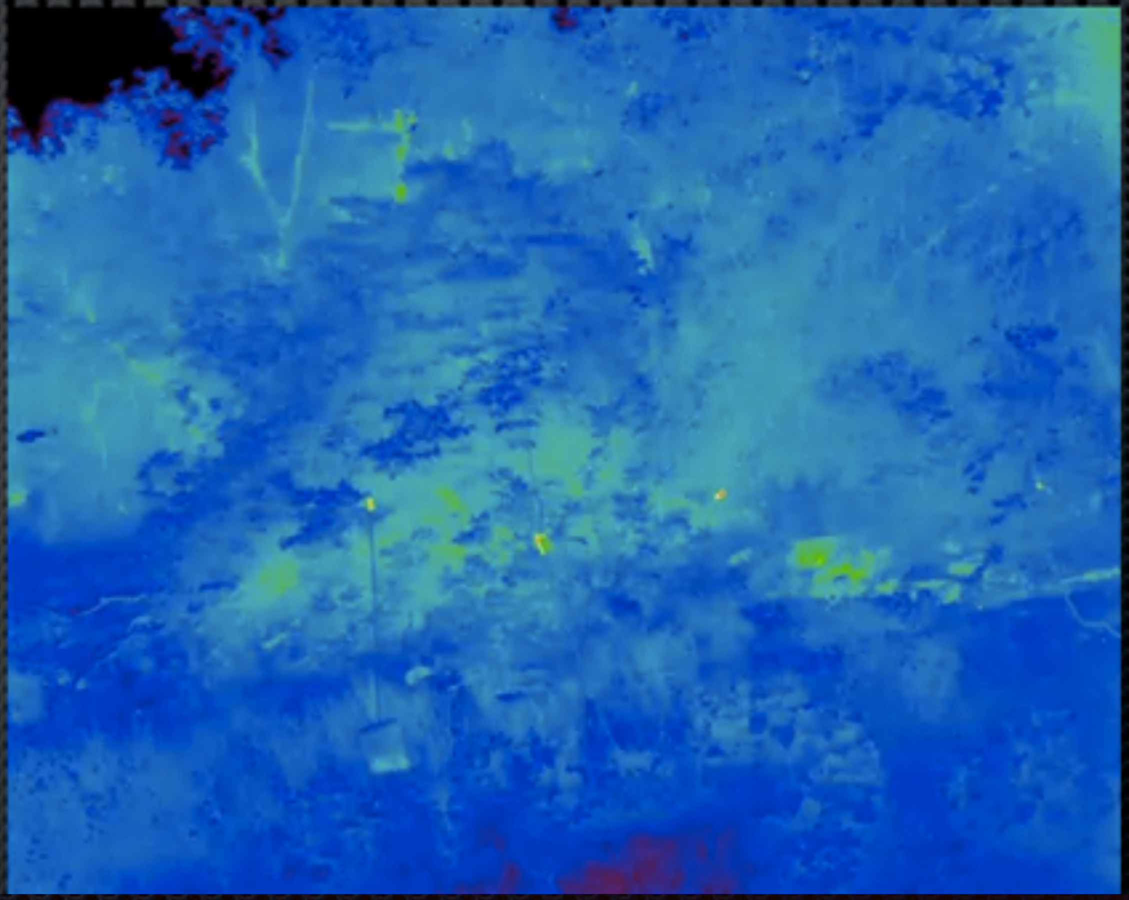


Perception-guided flight control - A two pronged attack

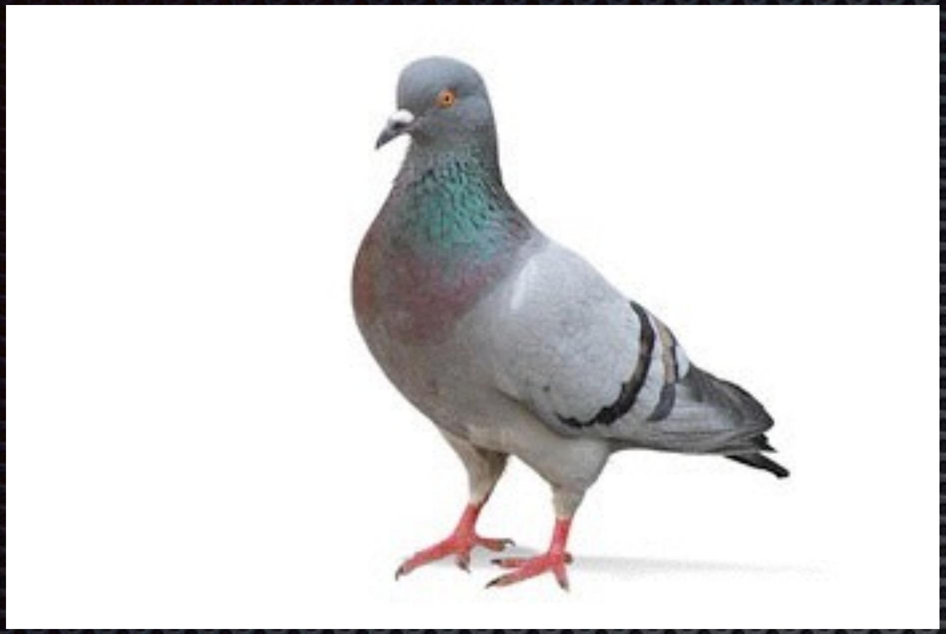
Understand how sensorimotor response changes with relative availability of visual information.



Fit various biologically plausible motion control laws to a large sample of actual animal flight data



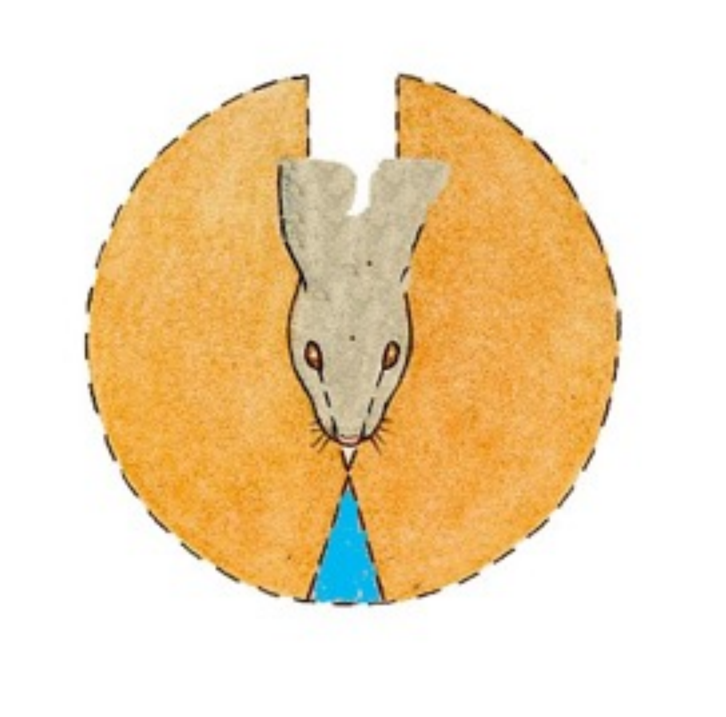
Perception-guided flight control - Animals of interest



Columba livia

Myotis velifer

Tadarida brasiliensis



Controlled motions through obstacle fields

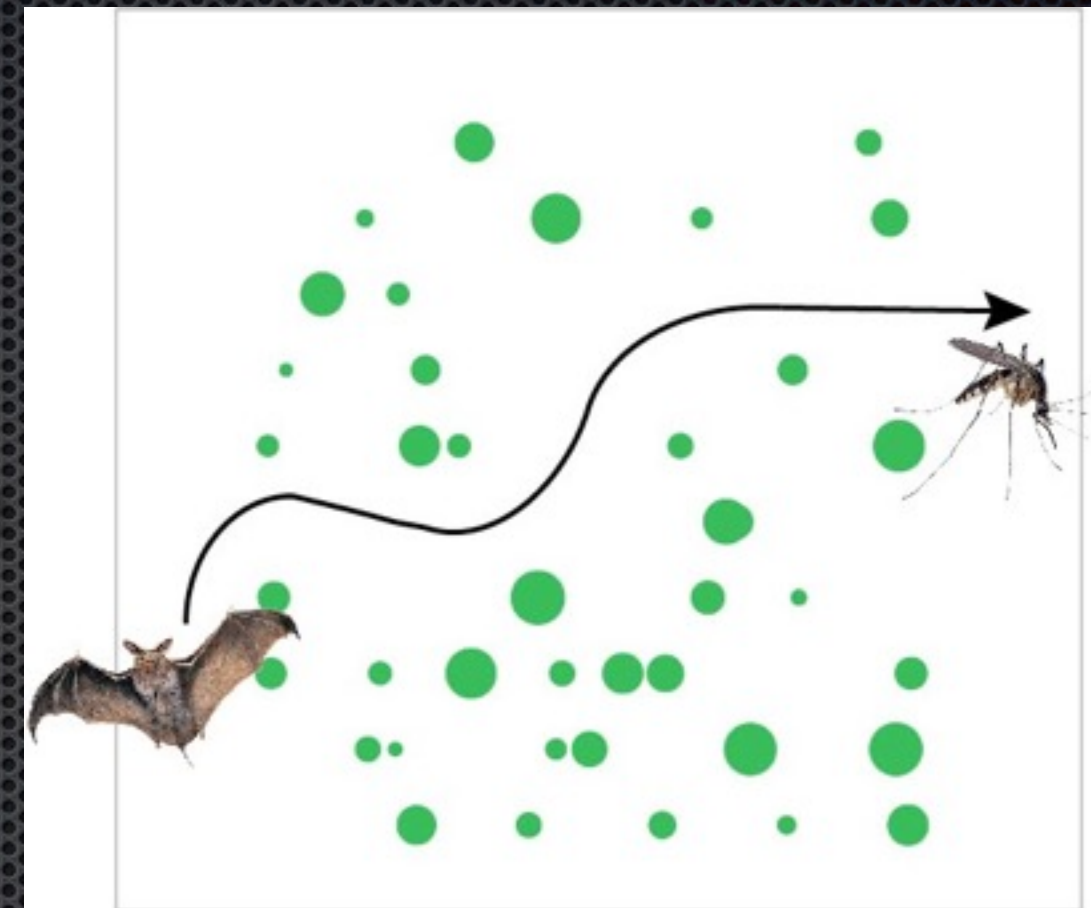
Bat motions are:

- Goal oriented (outer loop strategies)
- Highly reactive (inner loop strategies)
- Based on <u>perceptions</u> of the environment:

 Obstacles

 Other creatures

 Wind dynamics



Big question: Can trajectories reconstructed from field data be recreated using laboratory flight vehicles and sensors?

Studying bat flight behaviors in the field

Perception-guided flight control - Animals of interest

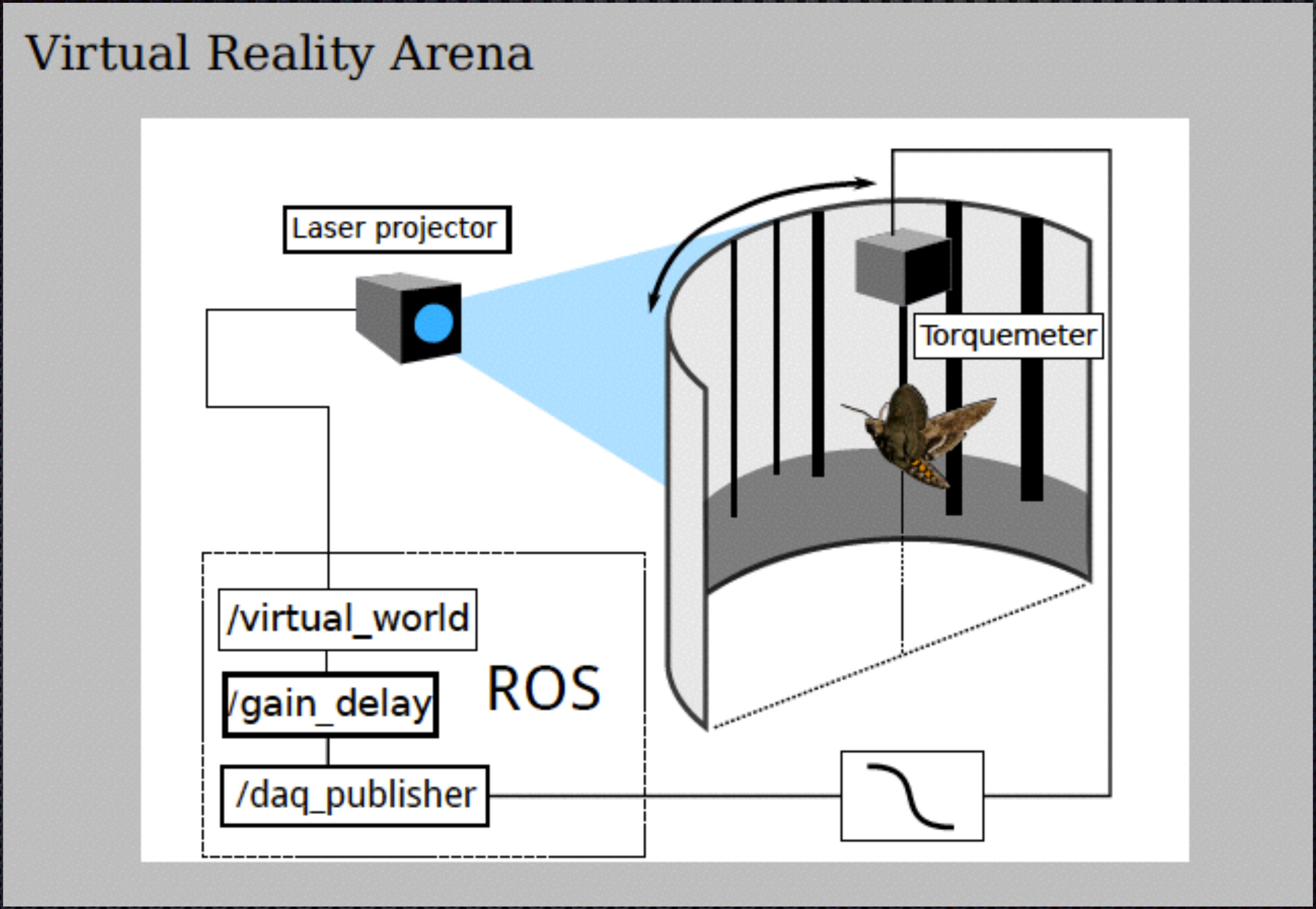
Manduca sexta

photo: Armin Hinterwirth

- Crepuscular flier
- Mass 2-3 g
- Wingspan 10 cm

Thanks to the Tom Daniels Lab, U. Washington

Studying insect flight behaviors in the lab



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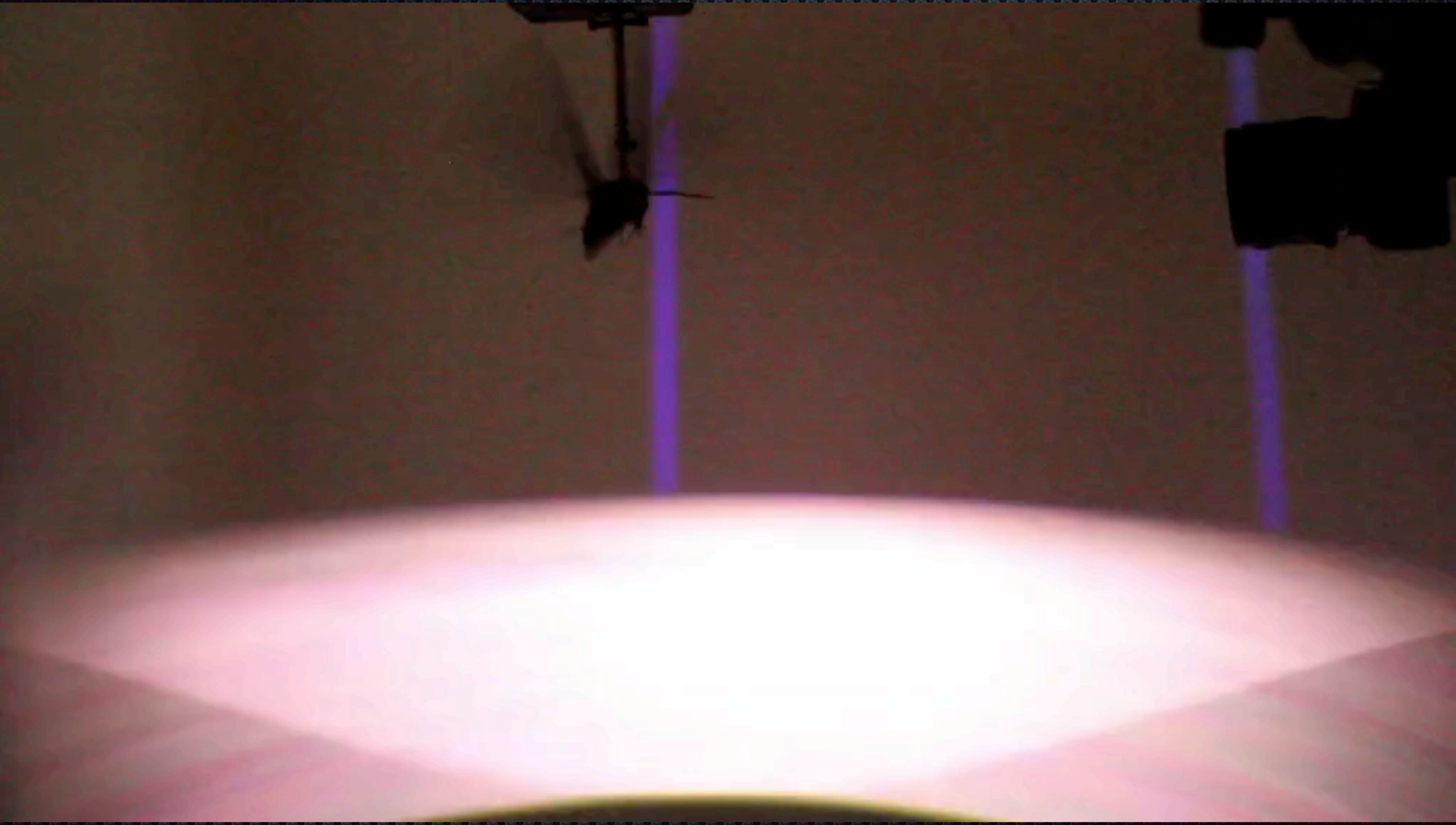

Tom Daniels Lab, U. Washington

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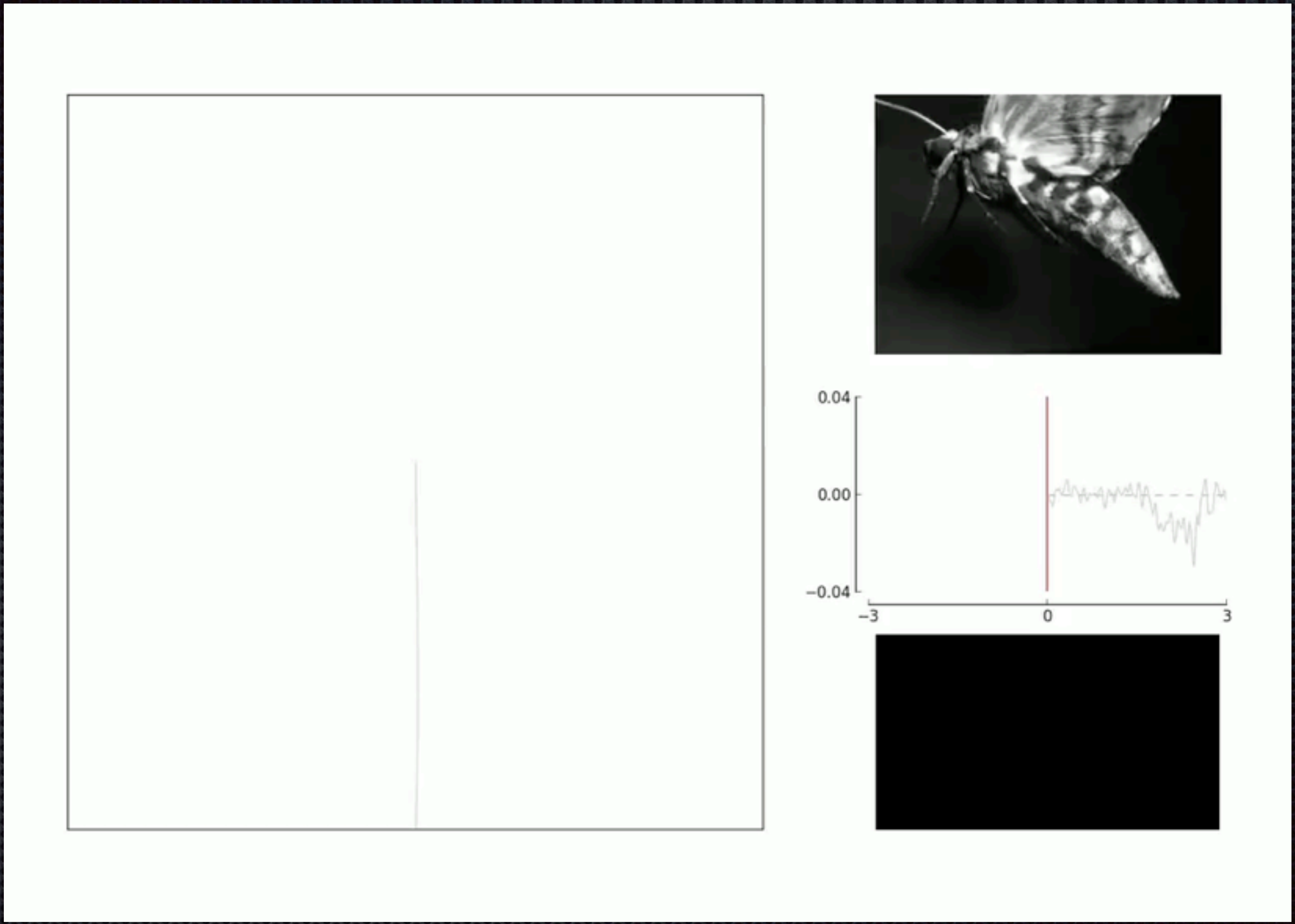

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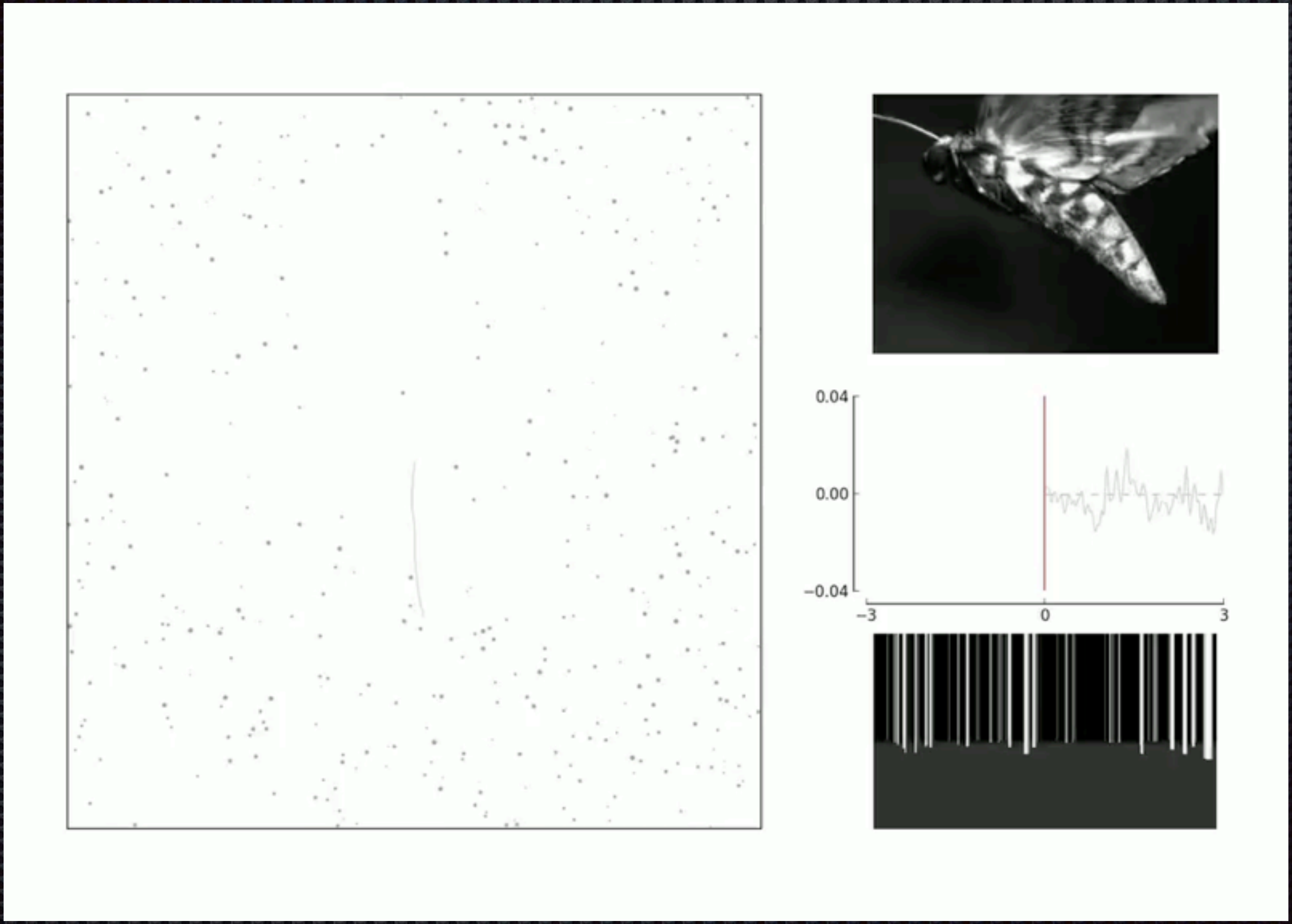
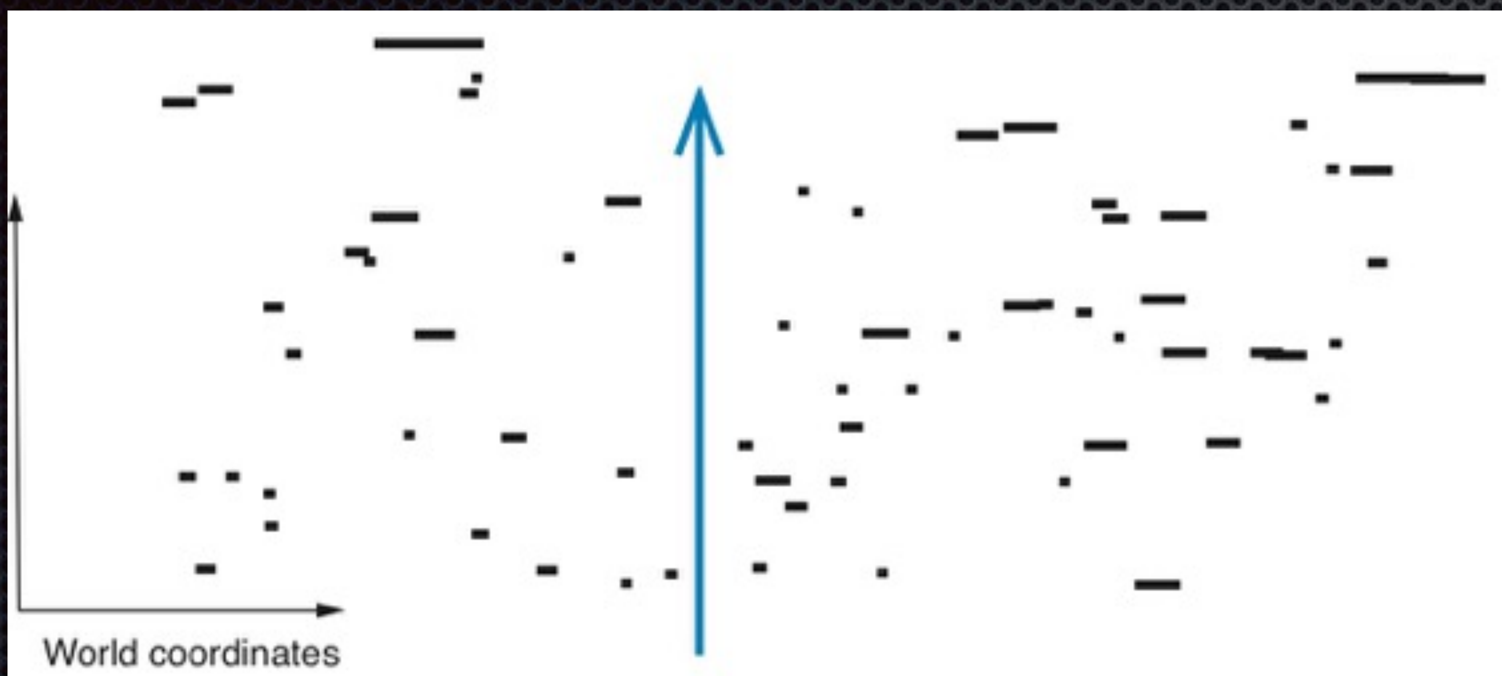


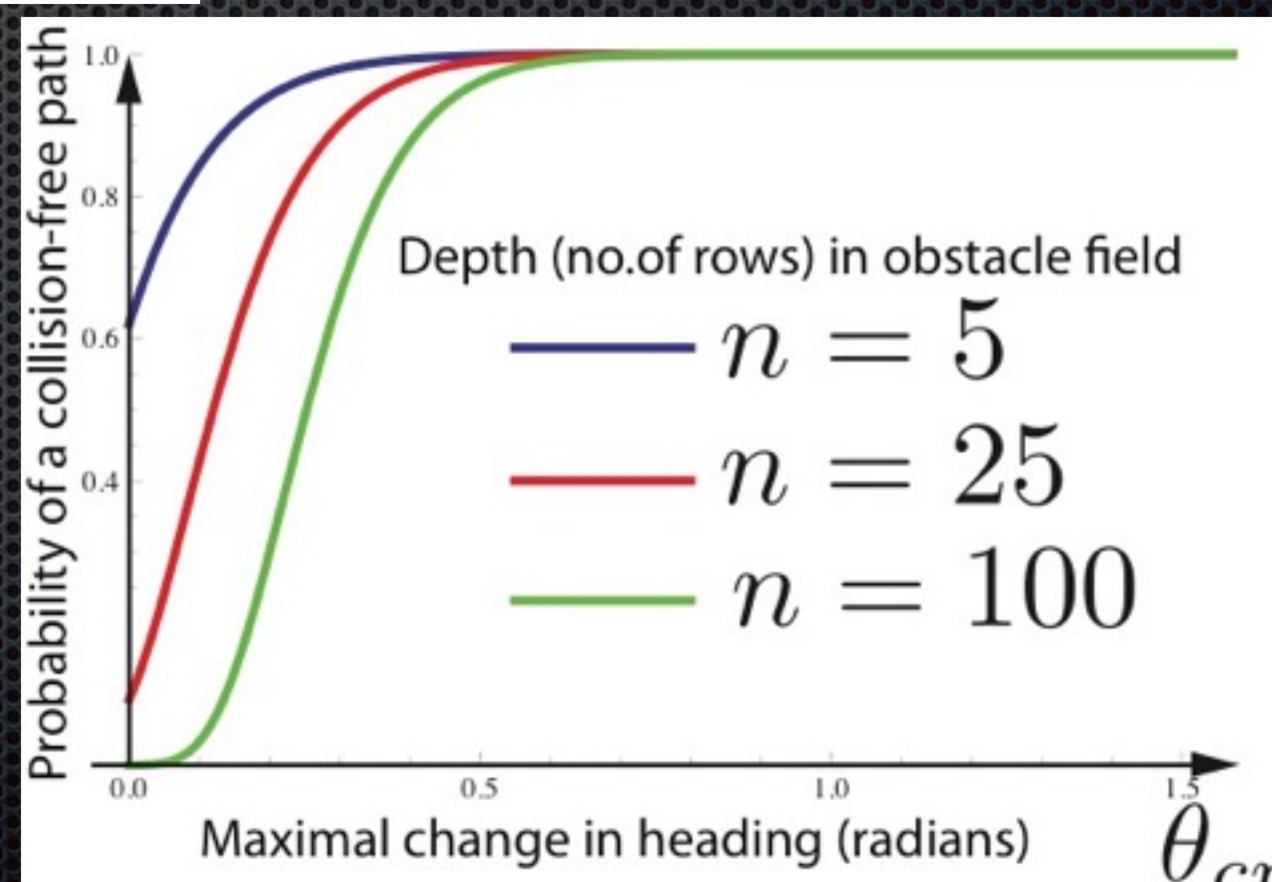
Tom Daniels Lab, U. Washington

Controlled motion through a simulated obstacle field



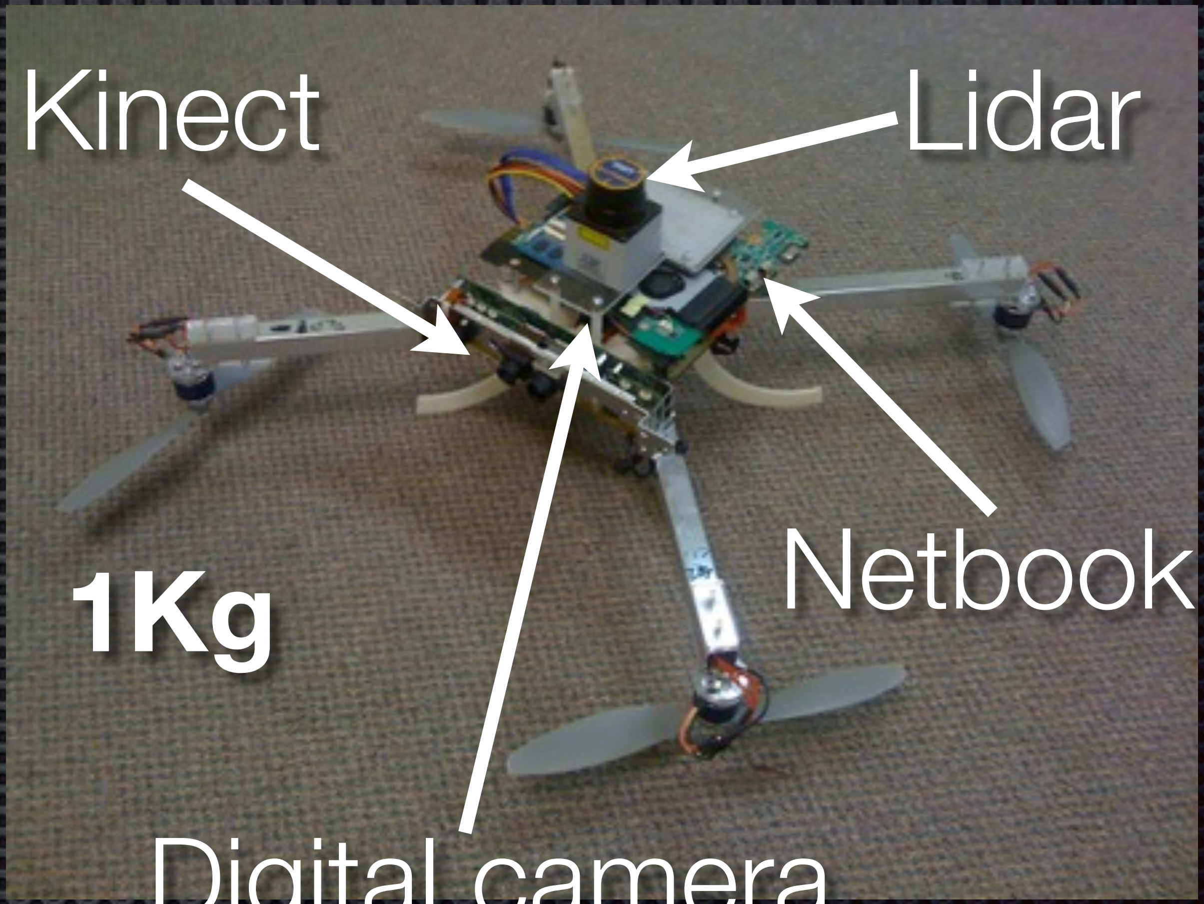
The obstacle widths follow and exponential distribution, as do the inter-obstacle spaces.

With the obstacle field as realized above, the probabilities of collision-free transit are



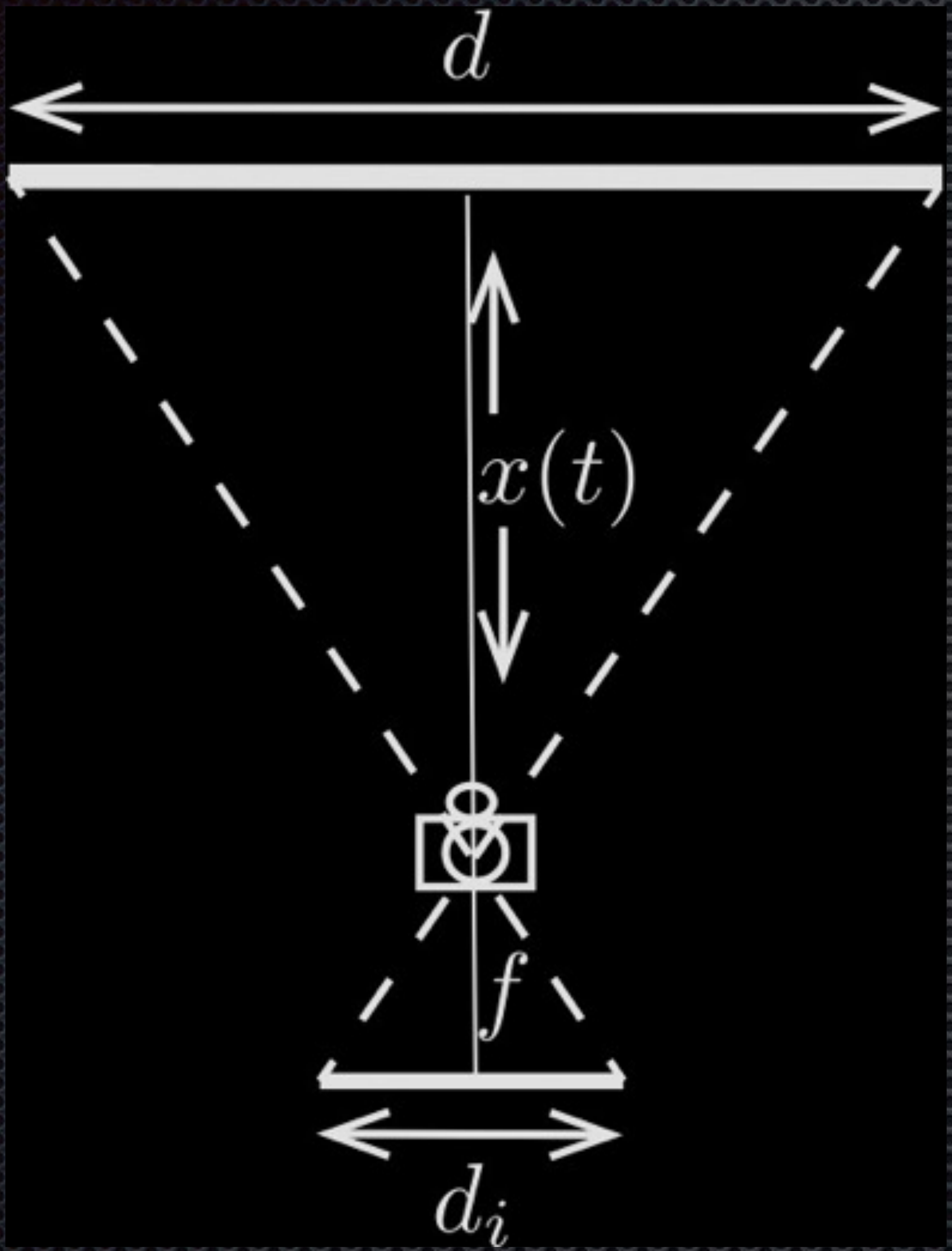
Animal-inspired perception-based motion control

- Perception-enabled motor control across behavior regimes in higher animals requires perception fusion;
- Understanding how specific perceptual cues enable specific flight behaviors seems attainable - "the devil is in the details".



Motion control based on optical flow sensing

Motion control based on optical flow sensing



Key assumption:

constant closing velocity

$$x(t) = x_0 - vt$$

impact occurs at $t = \tau$

s.t. $\tau = \frac{x_0}{v}$

by similar triangles

$$\tau = d_i / \dot{d}_i$$

Motion control based on optical flow sensing

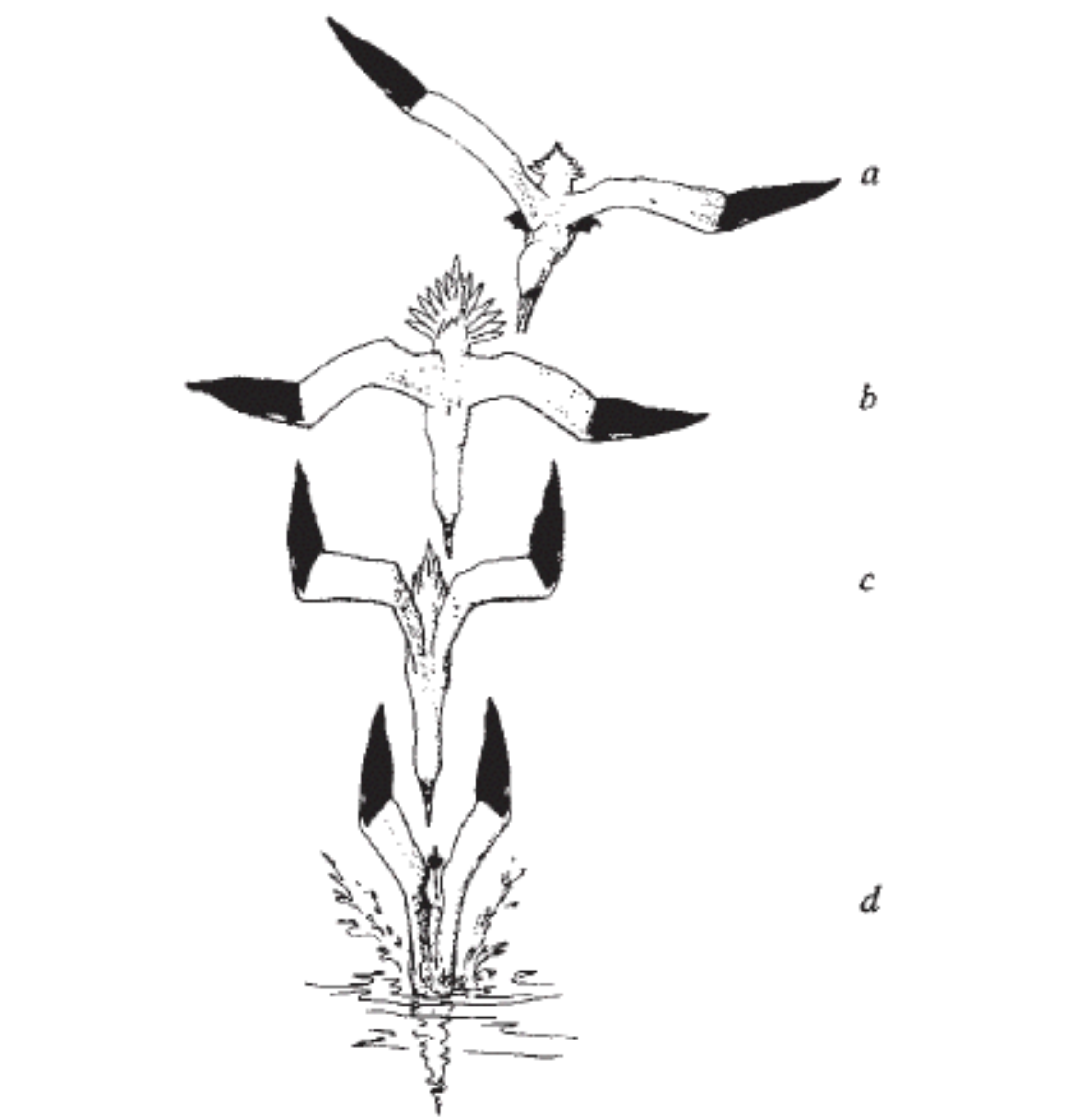
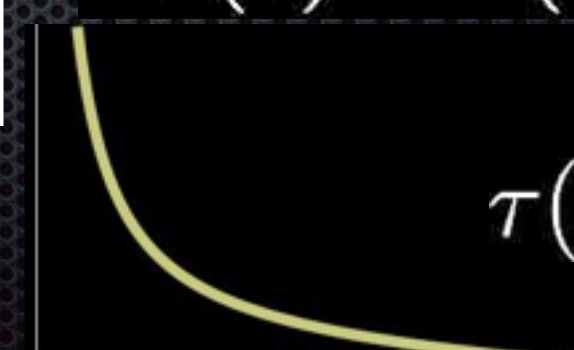


Fig. 2 Wing positions of diving gannet, *Sula bassana* (length ~0.9 m, wingspan 1.7 m). Illustration by John Busby. (Reprinted from ref. 7, courtesy of the author and publishers.)

D.N. Lee and P.E. Reddish, 1981. "Plummeting gannets: a paradigm of ecological optics," *Nature*, 293:293-294.

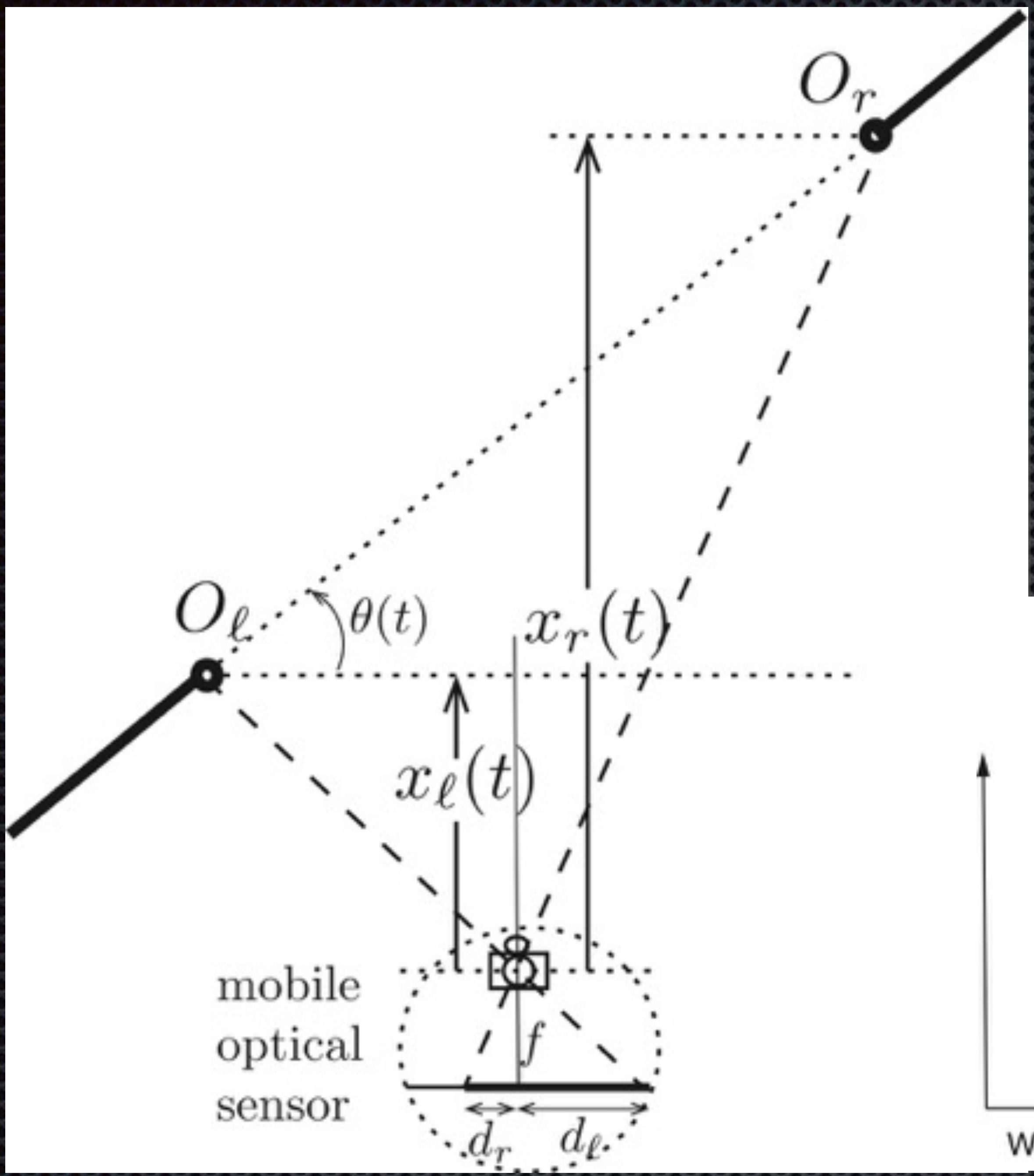
What if acceleration is constant?

$$\tau(t) = (t_d^2 - t^2)/2t$$

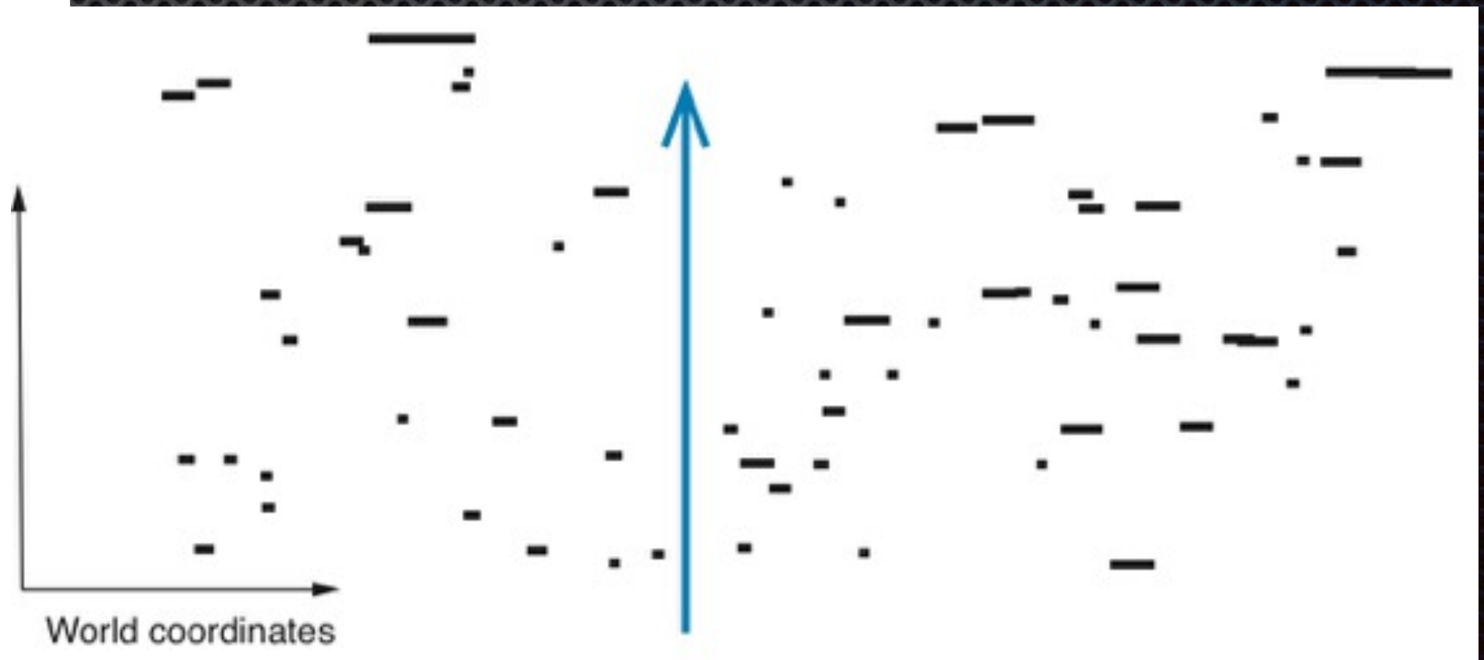


$$\tau(t_d - \epsilon) = \epsilon + o(\epsilon)$$

Motion control based on optical flow sensing

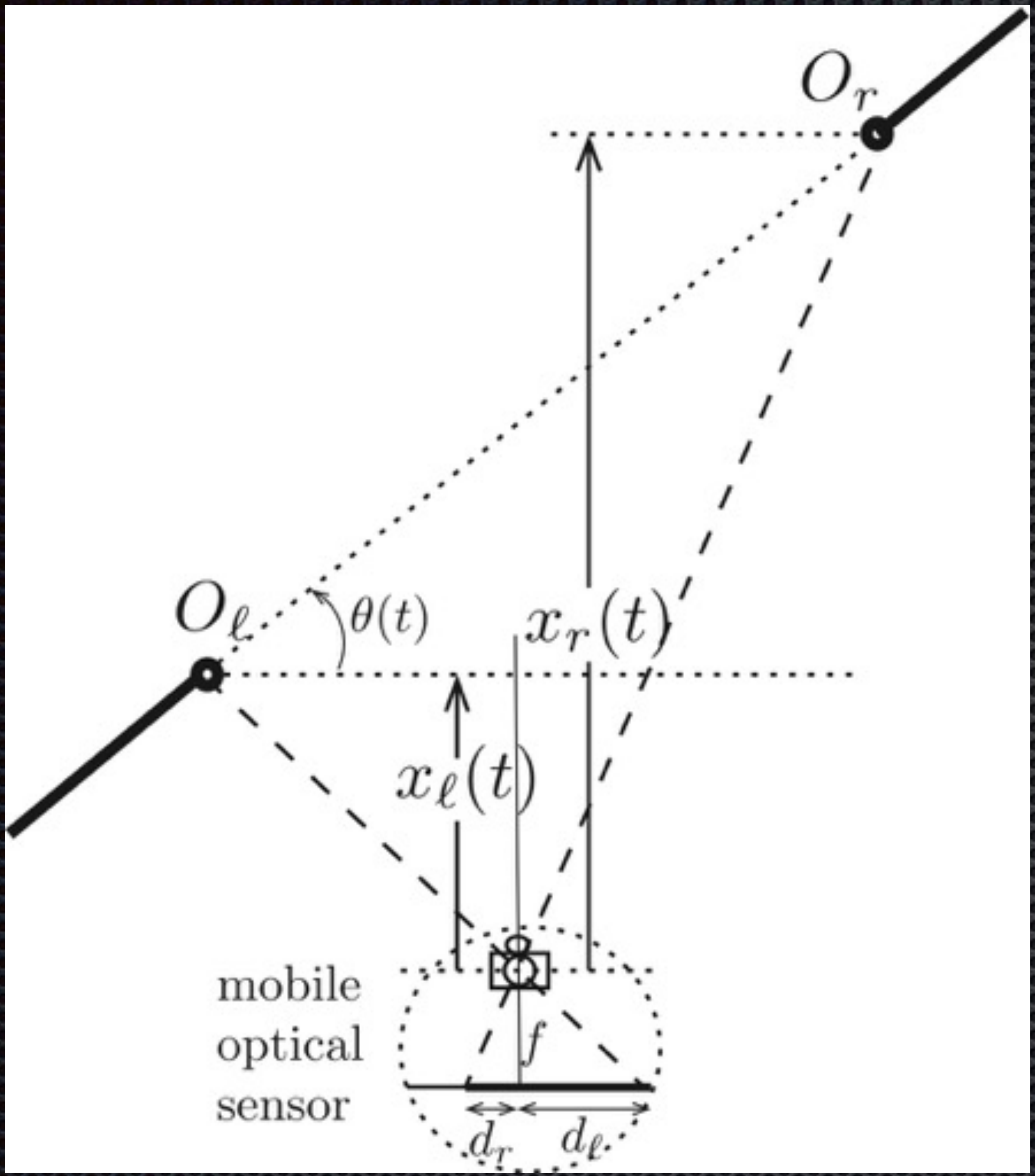


Heuristic:
Transit the open space in a direction perpendicular to obstacle row.

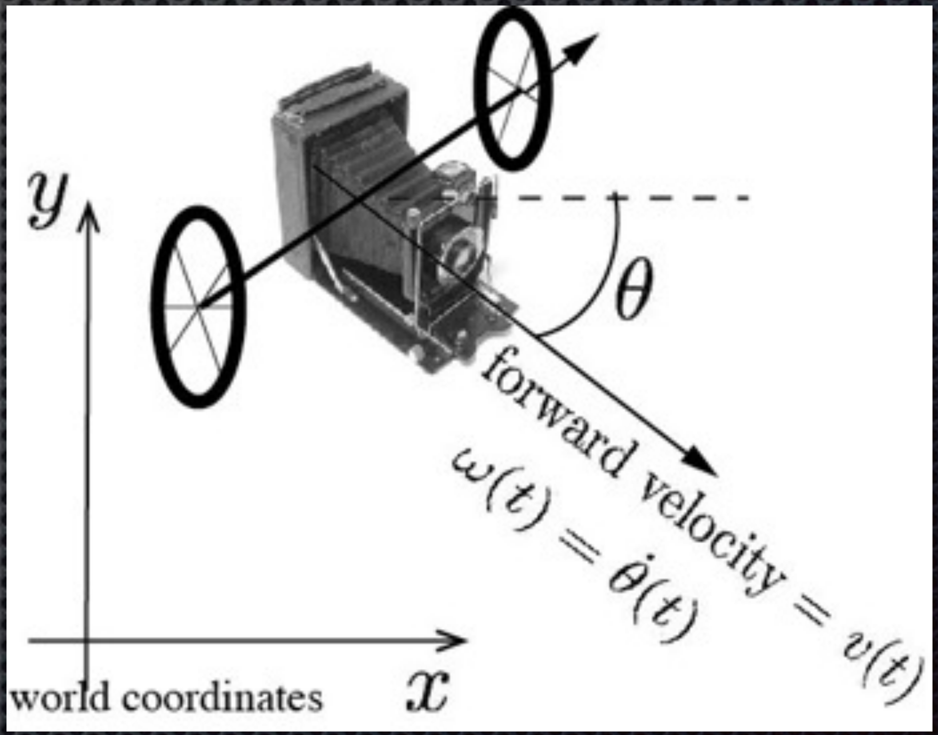


\tau is a proxy for distance.

Motion control based on optical flow sensing



$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} v(t)\cos\theta \\ v(t)\sin\theta \\ \omega(t) \end{pmatrix}$$



The values x_ℓ and x_r are not directly known.
Can we use τ_ℓ and τ_r as proxies?

Motion control based on optical flow sensing

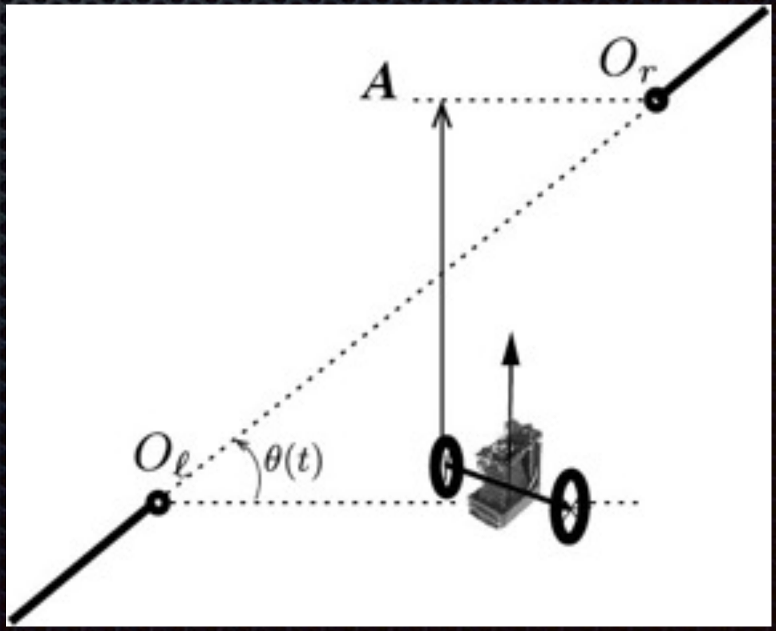
How we compute and think about $\tau_r(t)$

In terms of the mobile camera trajectory $(x(t), y(t), \theta(t))$,

$$\tau_r(t) = (\cos[\theta(t)](x_r - x(t)) + \sin[\theta(t)](y_r - y(t)) - 1)/v$$

Interpretation: Fictive trajectory

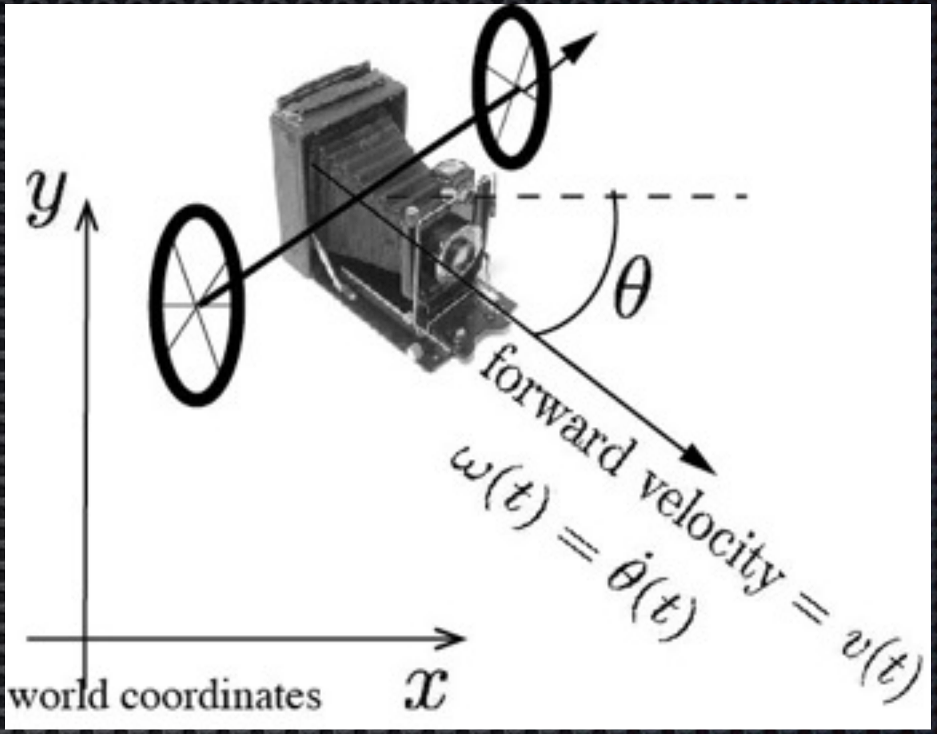
$$\begin{pmatrix} \hat{x}(s) \\ \hat{y}(s) \end{pmatrix} = \begin{pmatrix} x(t) + vs\cos\theta(t) \\ y(t) + vs\sin\theta(t) \end{pmatrix}$$



transits line A when $s = \tau_r(t)$.

Motion control based on optical flow sensing

$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} v(t)\cos\theta \\ v(t)\sin\theta \\ \omega(t) \end{pmatrix}$$



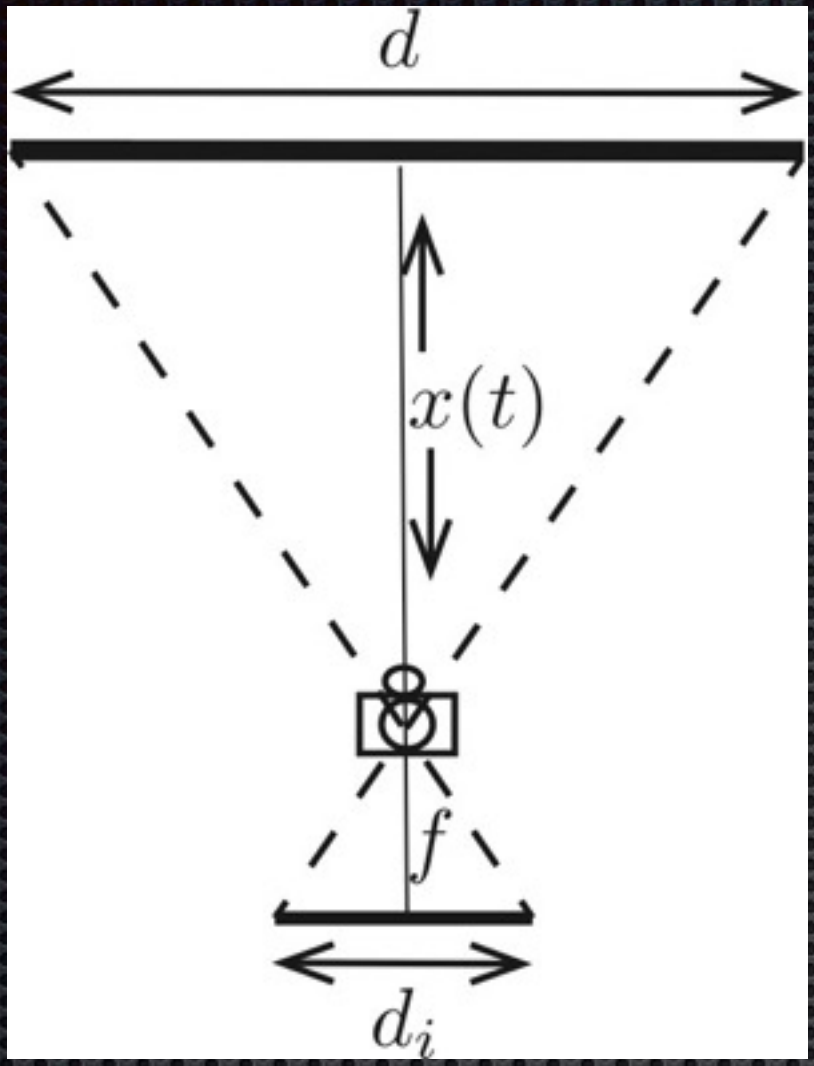
Theorem: Consider the camera motion kinematics as above. Let $\epsilon > 0$ be a small positive constant. The image-referenced configuration set

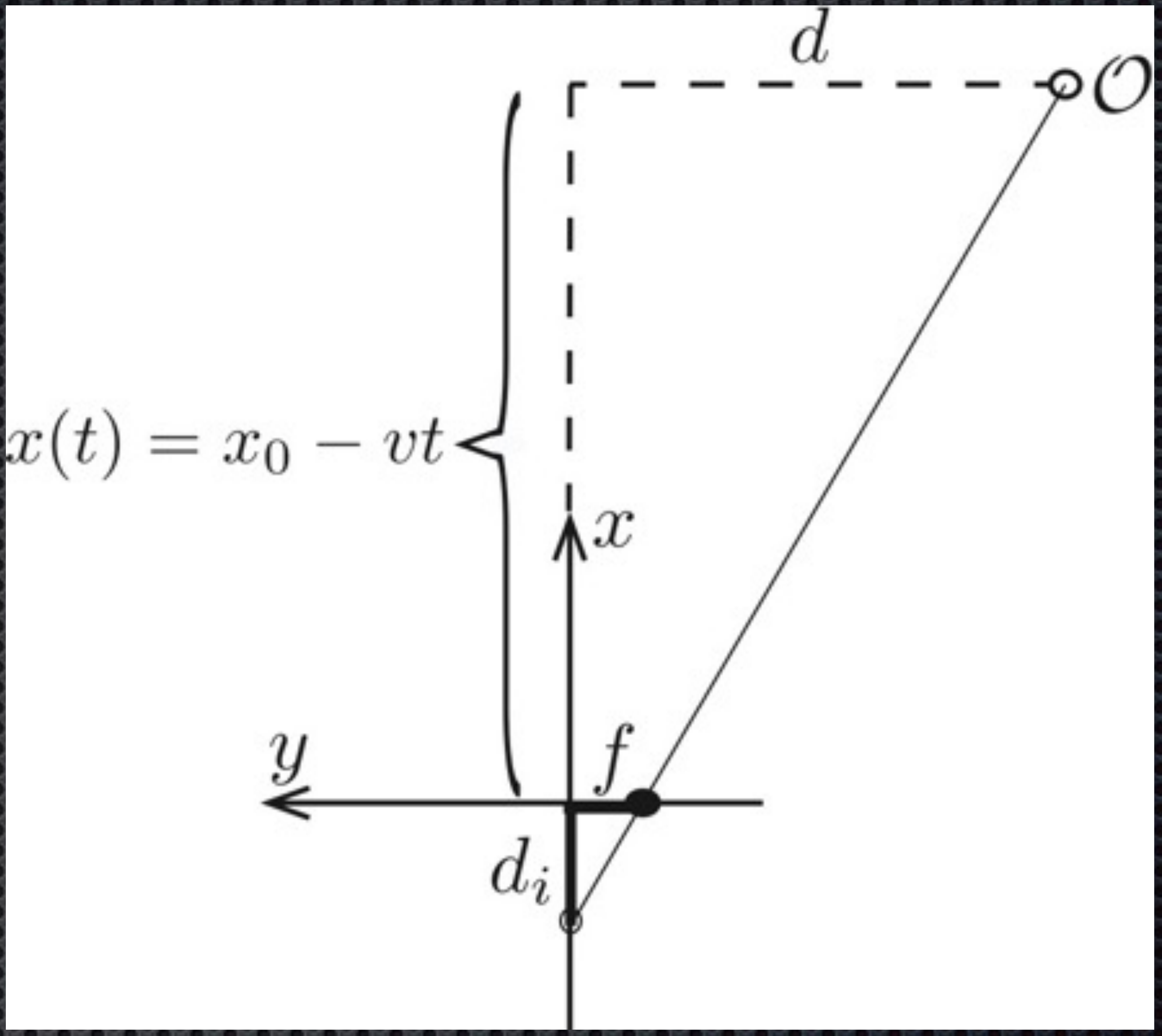
$$d_\ell \le -\epsilon \text{ and } \; d_r \ge \epsilon \tag{1}$$

is invariant under the feedback control law

$$\begin{aligned} v(t) &= \min(1, \tau_\ell + \tau_r) \\ \omega(t) &= \begin{cases} 0 & \text{if} \quad d_r = \epsilon \text{ or } d_\ell = -\epsilon \\ \tau_r - \tau_\ell & \text{if} \quad d_r > \epsilon \text{ and } d_\ell < -\epsilon. \end{cases} \end{aligned}$$

τ for idealized eye geometries

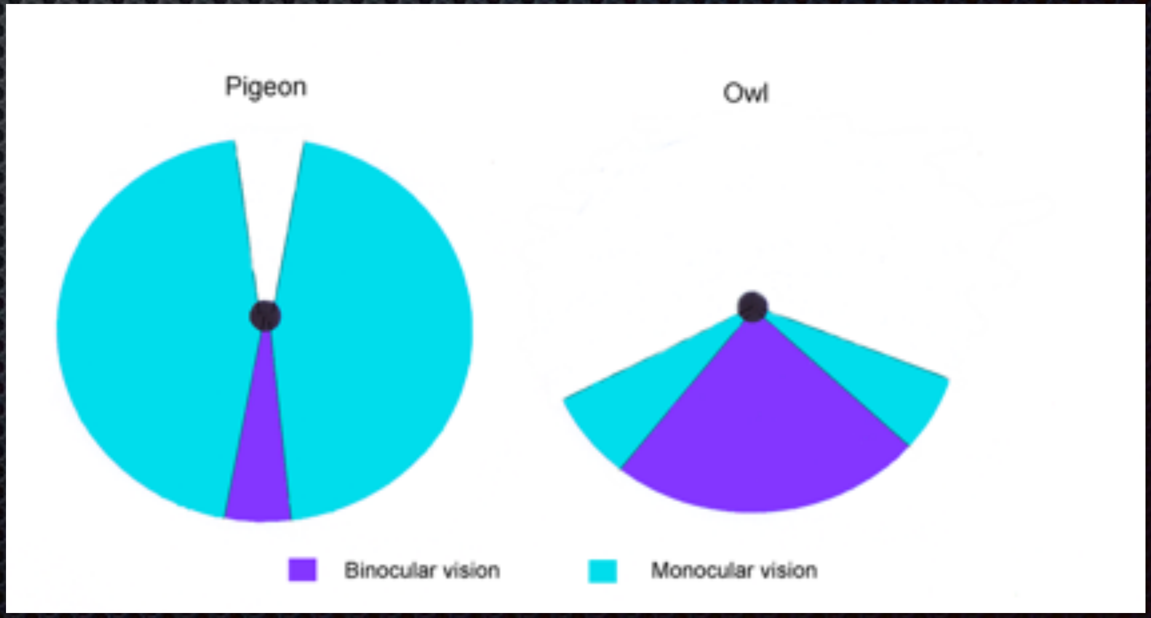




$$\tau = \frac{d_i}{\dot{d}_i}$$ = time-to-transit

Sensory information

- Echolocation
- ~~Binocular vision~~
- Optical flow
- Dead reckoning (spatial memory)
- Response to ambient airflow



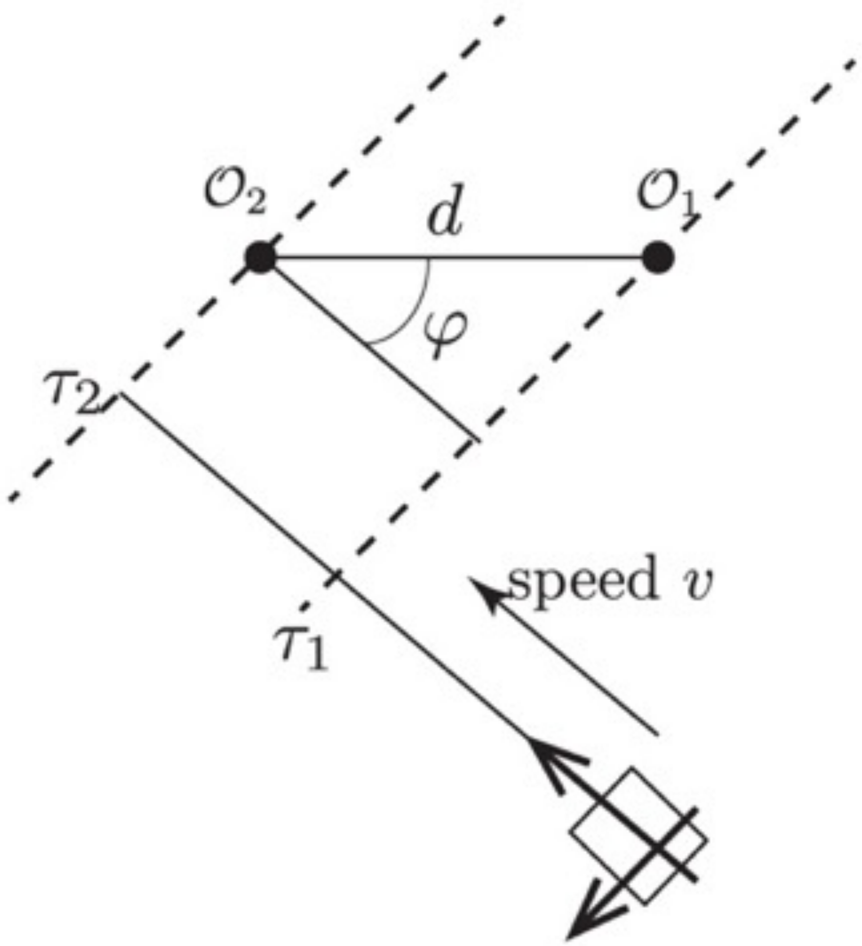
τ for "all" eye geometries

$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} v\cos\theta \\ v\sin\theta \\ u \end{pmatrix}, \qquad \tau = \frac{d_i}{\dot{d}_i}$$

τ is a purely configuration-dependent quantity

$$\boxed{\tau = \frac{\cos\theta\,(x_w - x) + \sin\theta\,(y_w - y)}{v}.}$$

Motion control based on optical flow sensing



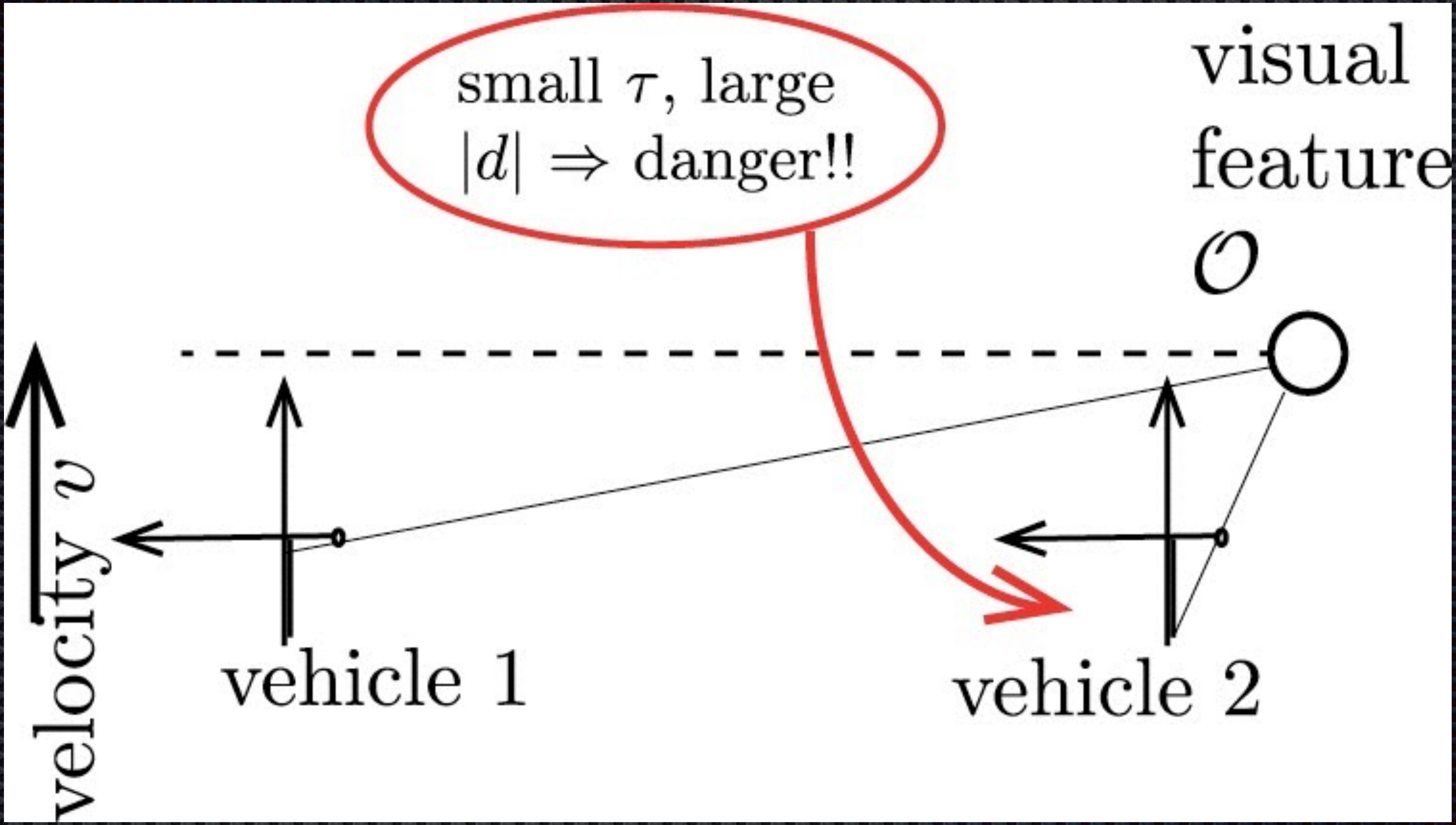
Theorem

Let $\tau_j(t)$ be the time-to-transit associated with feature $\mathcal{O}_j$ for $j = 1, 2$. Suppose the initial orientation, θ_0, of the vehicle is such that $\tau_2 > \tau_1$. Further assume that the vehicle travels at constant speed $v = 1$. Then for any $k > 0$, the steering control

$$u = u(t) = k\left[{\tau_2}'(\theta(t)) - {\tau_1}'(\theta(t))\right],$$

where $\tau_j'(\theta) = \frac{\partial \tau_j}{\partial \theta}$, will asymptotically align the vehicle with the semi-infinite line directed from $\mathcal{O}_1$ to $\mathcal{O}_2$.

Distance cues in optical flow



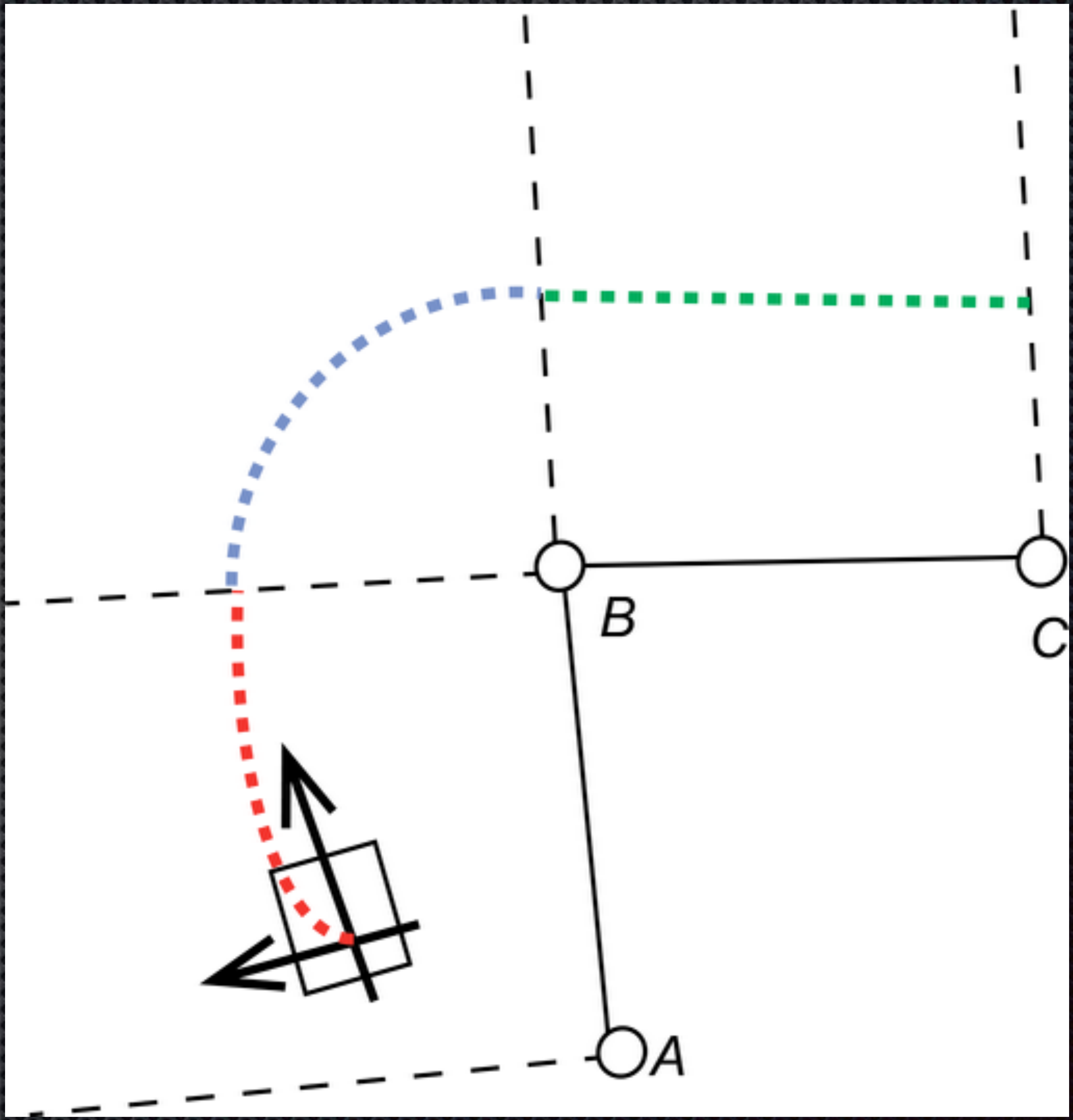
τ is the same, but the feature image lies on a different part of the retina.

A *tau*-based control library

Time-to-Transit vision-based steering controls		
$u_c[\mathcal{O}]$	single-feature control —feature circling	keeps $\tau_{\mathcal{O}}$ constant follows circular arc at constant radius from feature $\mathcal{O}$.
$u_d[\mathcal{O}_1, \mathcal{O}_2]$	paired-feature control —distance maintenance	aligns with the line segment from $\mathcal{O}_1$ to $\mathcal{O}_2$; see Theorem above.
$u_p[\mathcal{O}_1, \mathcal{O}_2]$	paired feature control — steers between features	control law from [*CDC 12, Sebesta and Baillieul*] to steer vehicle on path between $\mathcal{O}_1, \mathcal{O}_2$.

Optical flow based steering protocol

- Align with *AB*;
- Circle *B* until aligned with *BC*;
- Fly parallel to *BC*.



Animal-inspired perception-based motion control

Toward understanding how specific cues enable specific flight behaviors

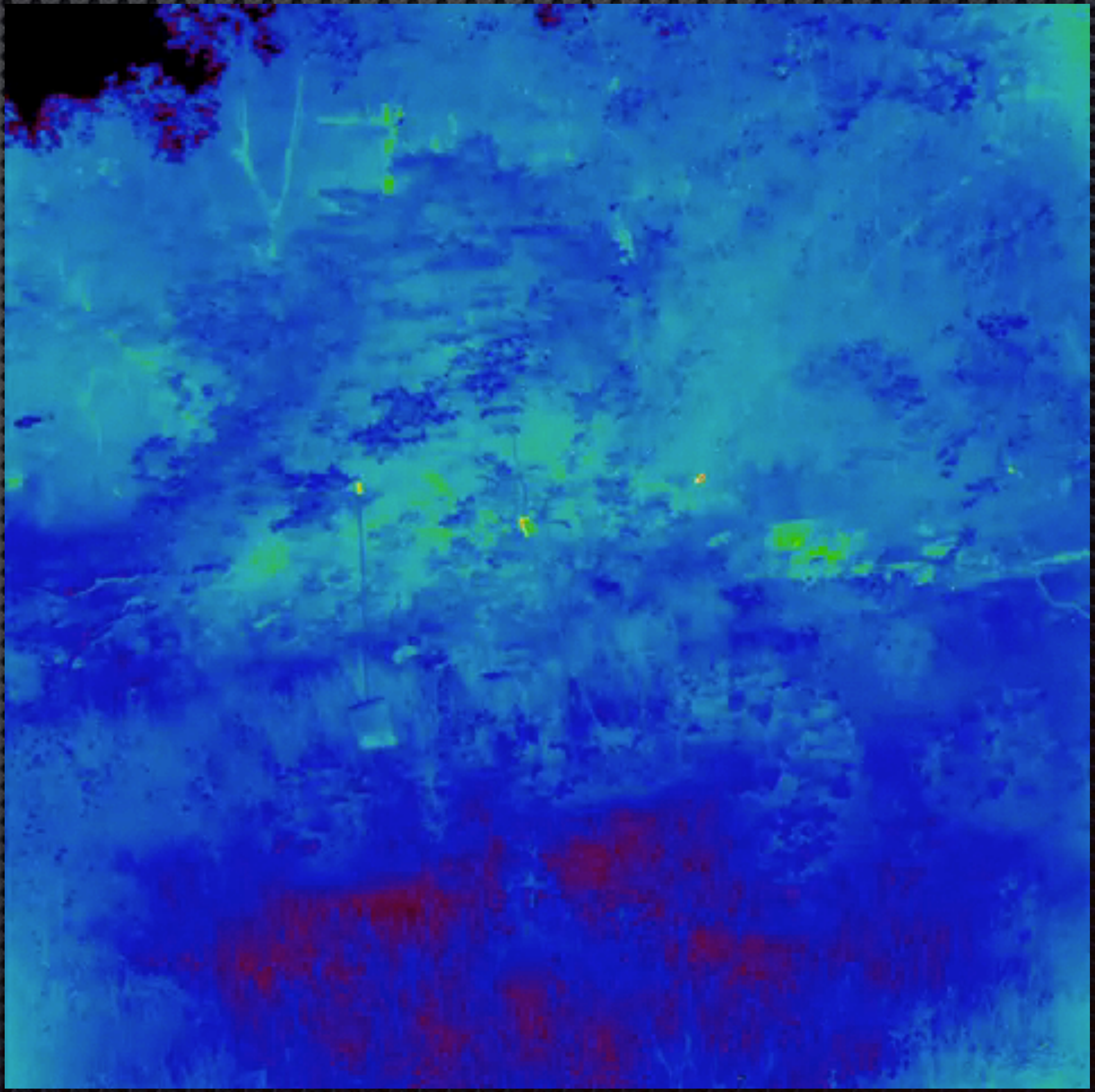
Bio-inspired vision-based perception:

• Sparse optical flow	suitable for real-time flight through sufficiently textures rich visual settings
• Dense optical flow	primarily off-line video processing
Time-to-contact	algorithms needed for dynamically rich settings

The setting for our study of bat flight trajectories:

405 *Mytois velifer* bats emerging from a cave in the Bamberger ranch preserve in Johnson City, Texas.

- High-resolution thermal video recordings were mined to reconstruct three-dimensional flight paths of 405 different trajectories.
- Spline smoothing to correct for errors.
- Trajectories projected to 2-D.
- Reparameterization by arc length.



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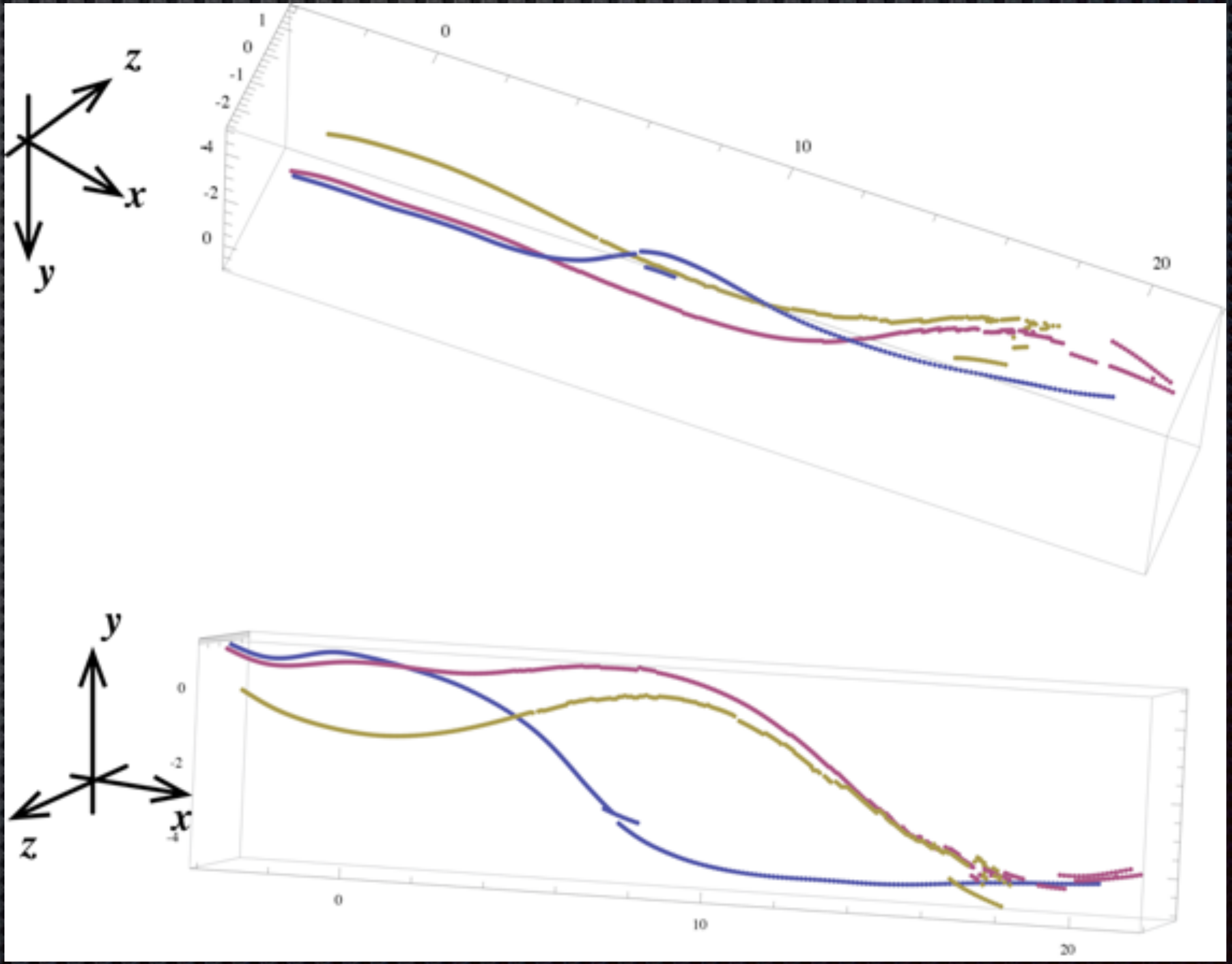

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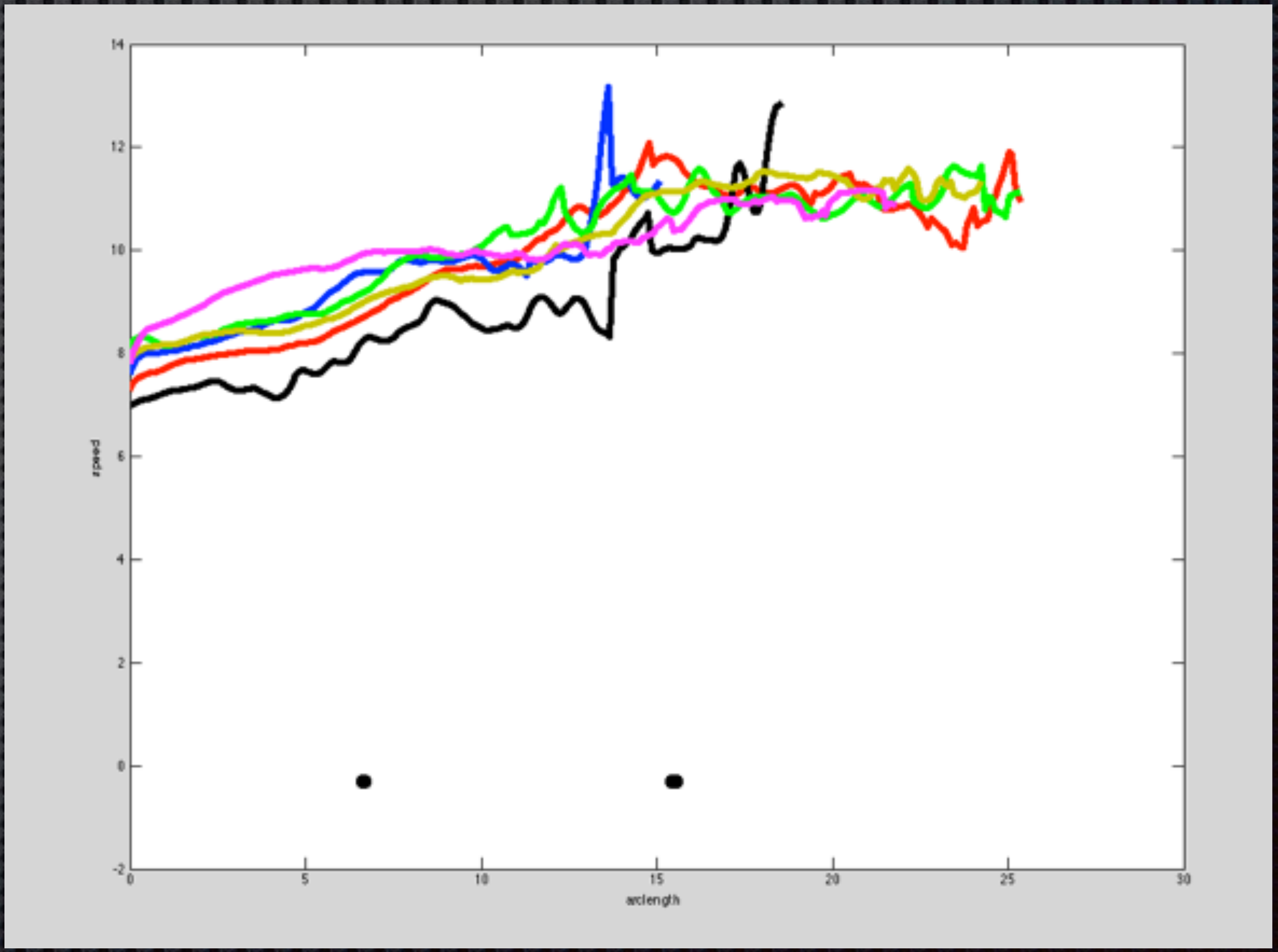
- Flight speeds do not vary much.



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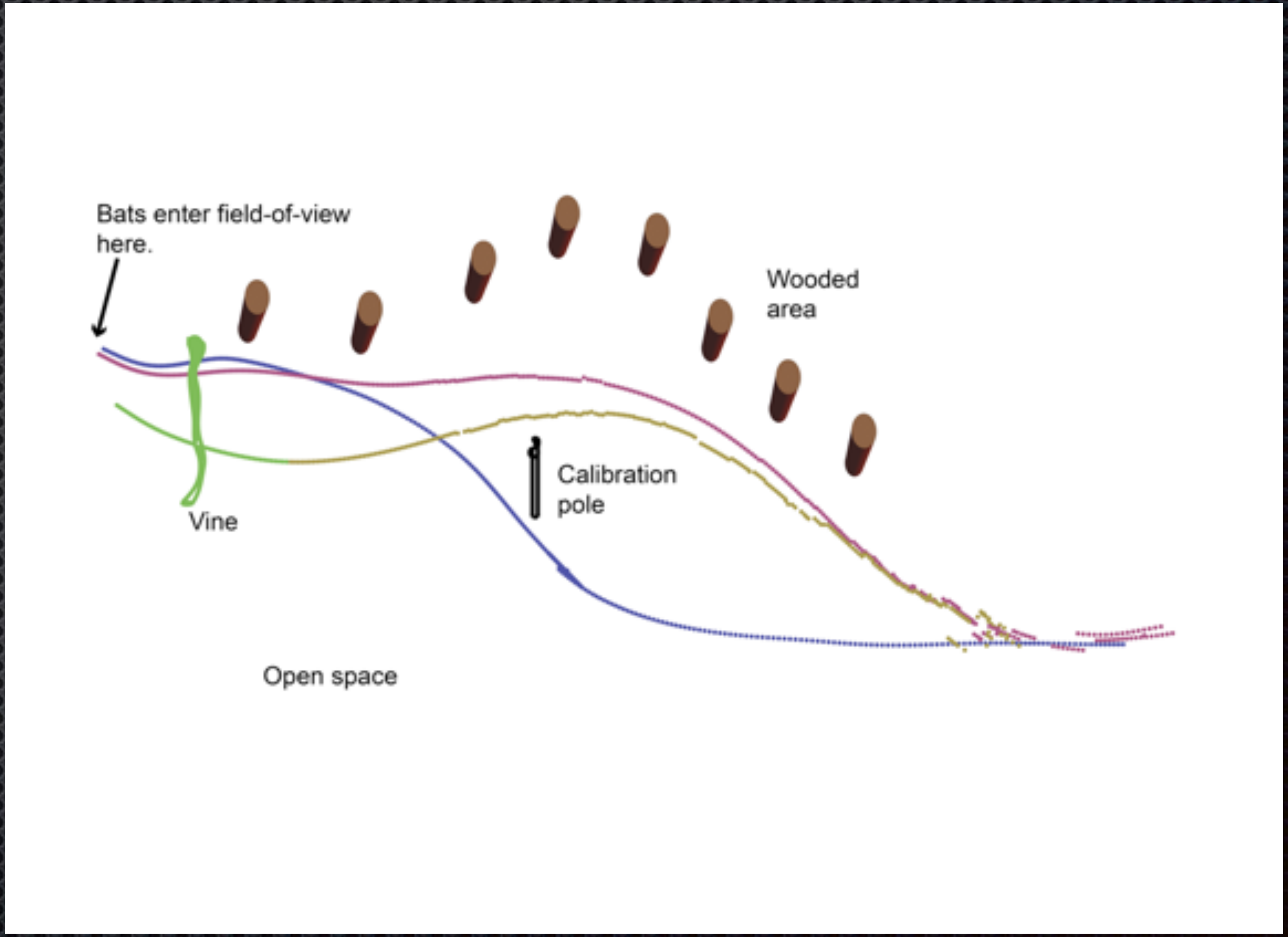

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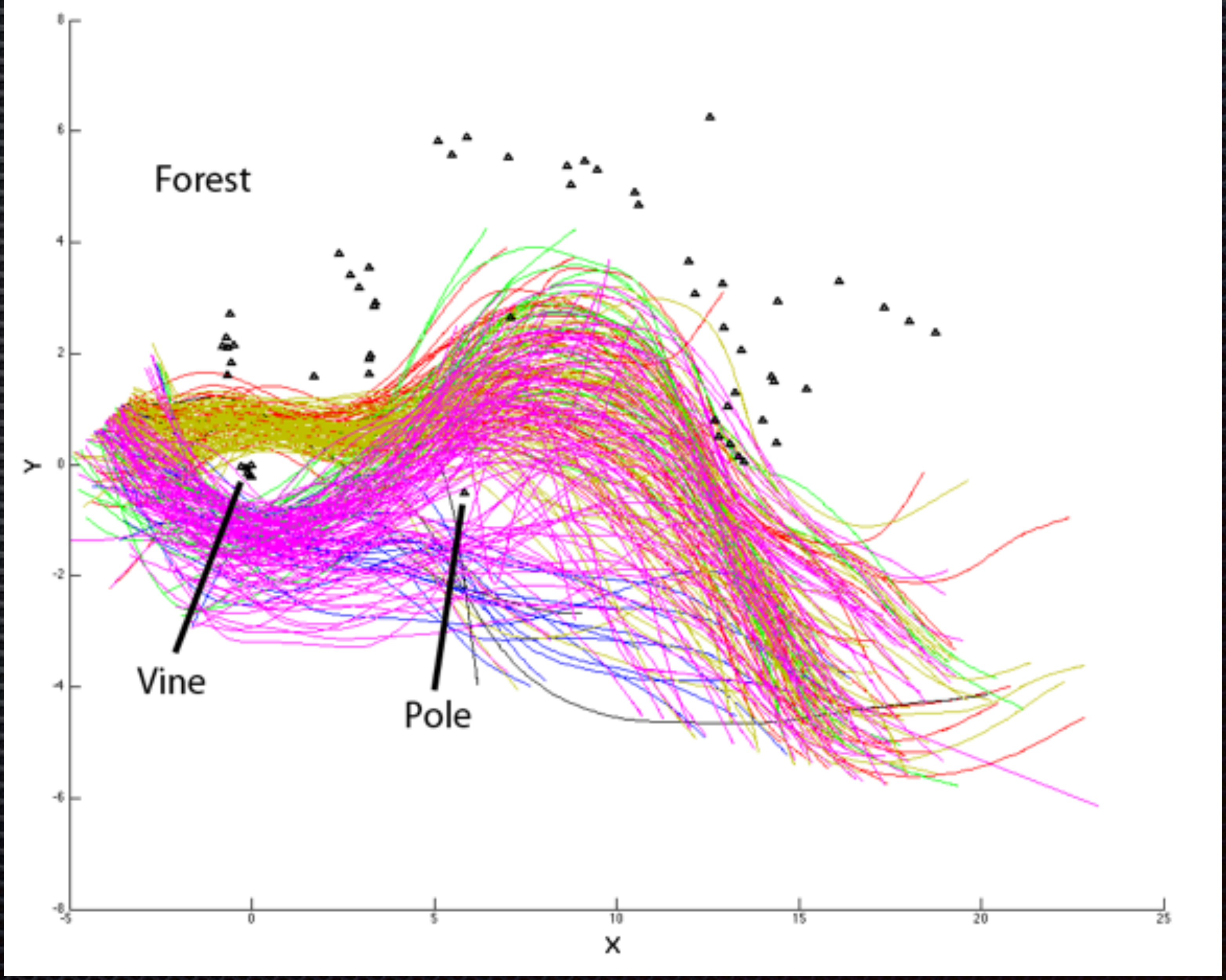
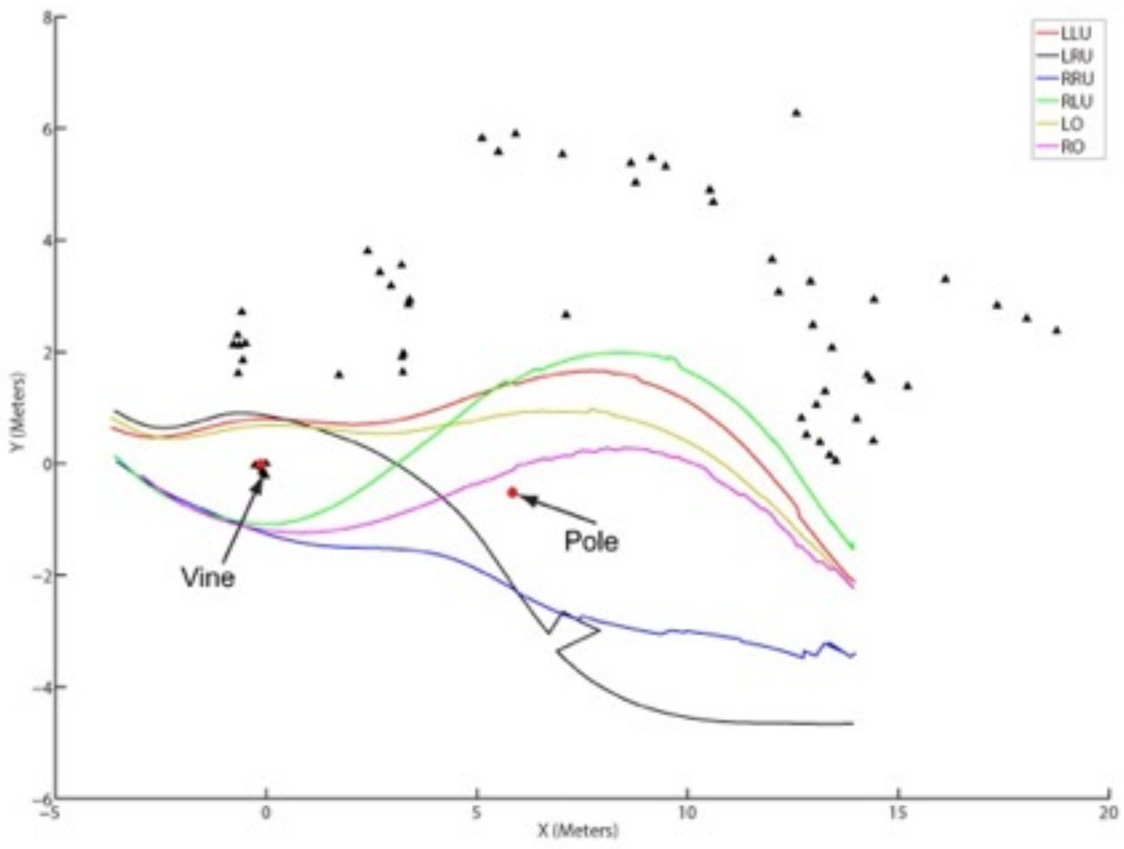


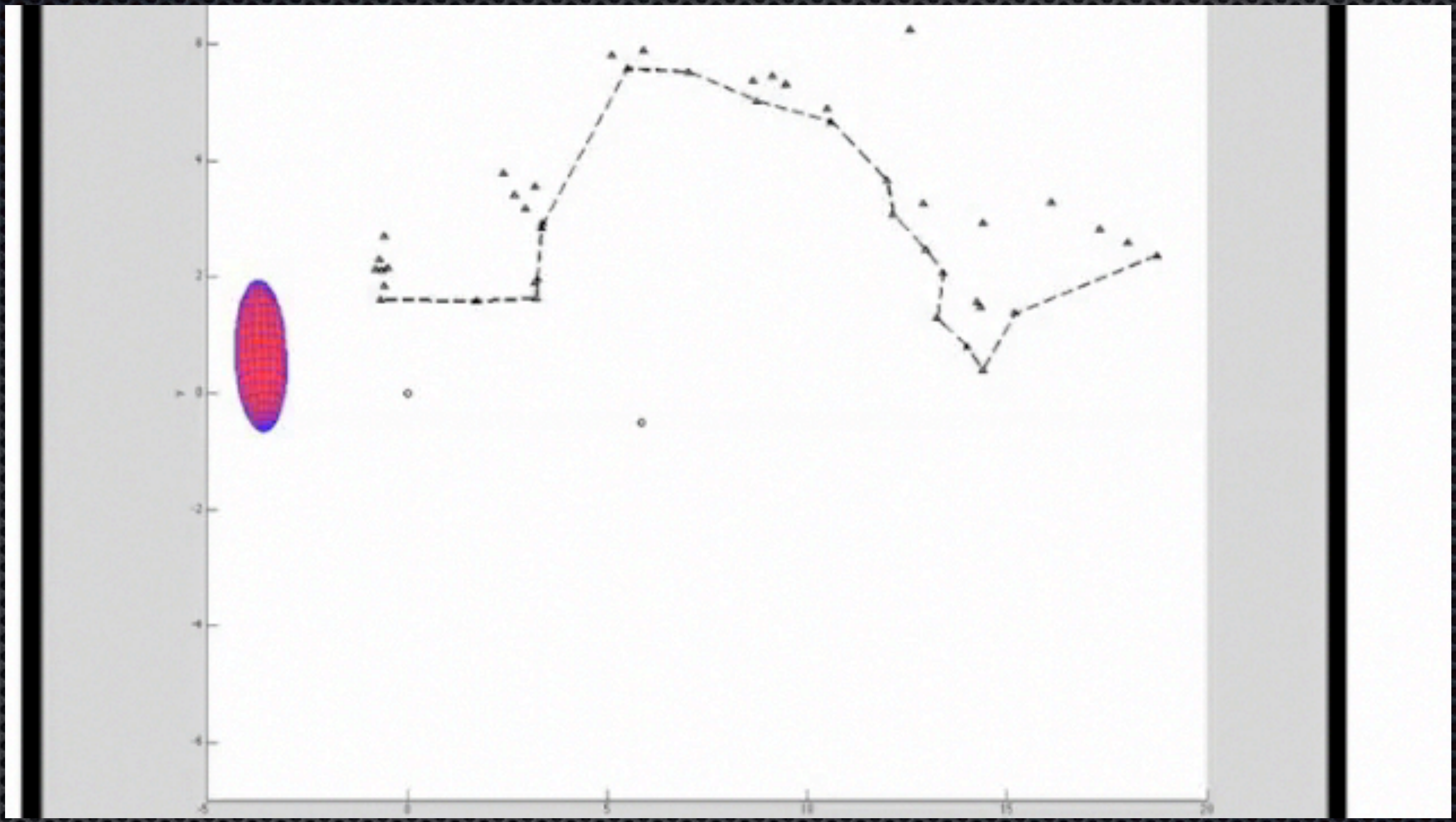
254 *M. velifer* trajectories averaged according to avoidance strategies



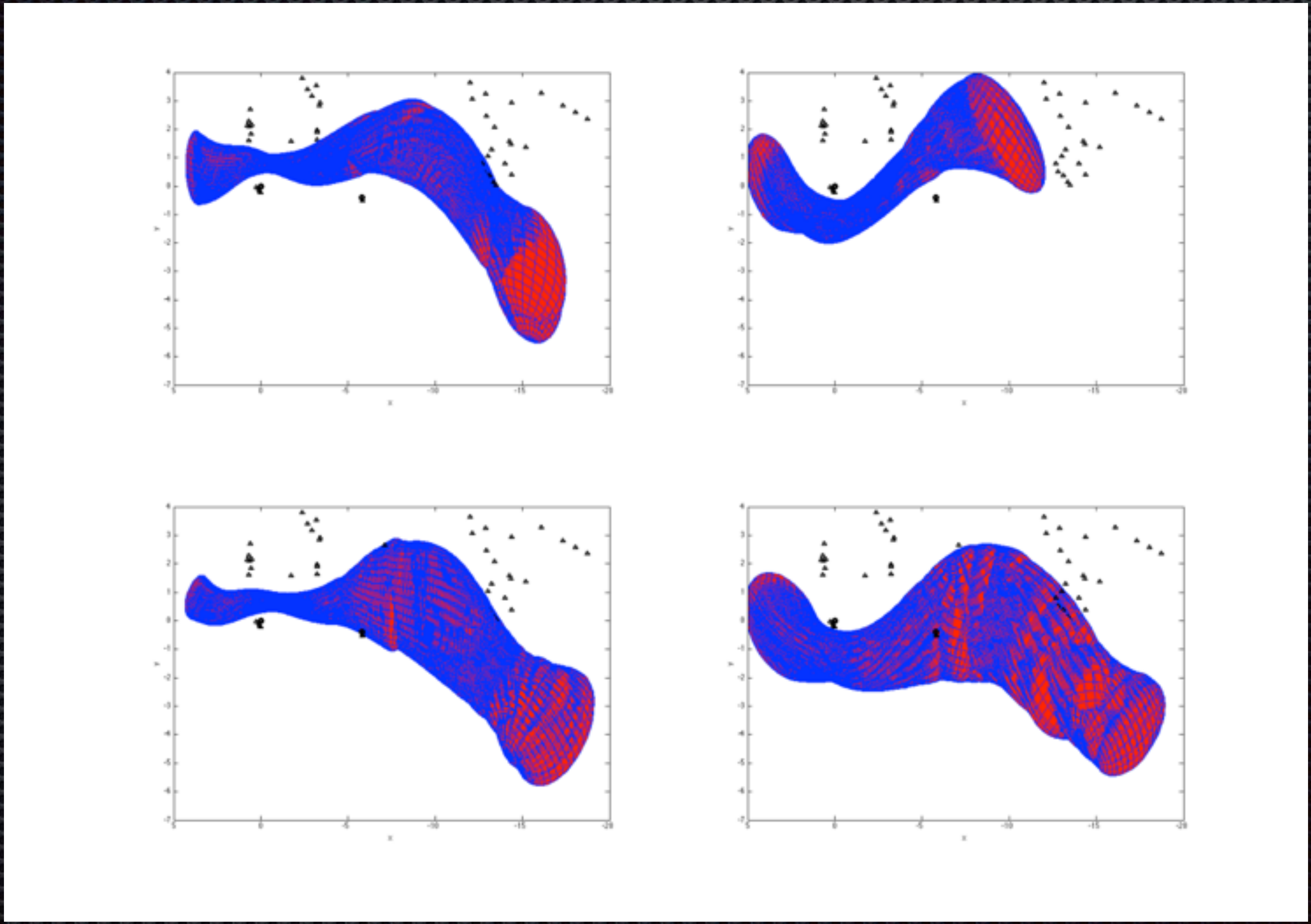
Trajectories are parameterized by arc-length.

Number for Each Group		
Group	Number	Percentage
LLU	39	15.35
LRU	3	1.18
RRU	14	5.51
RLU	27	10.63
LO	73	28.74
RO	98	38.58

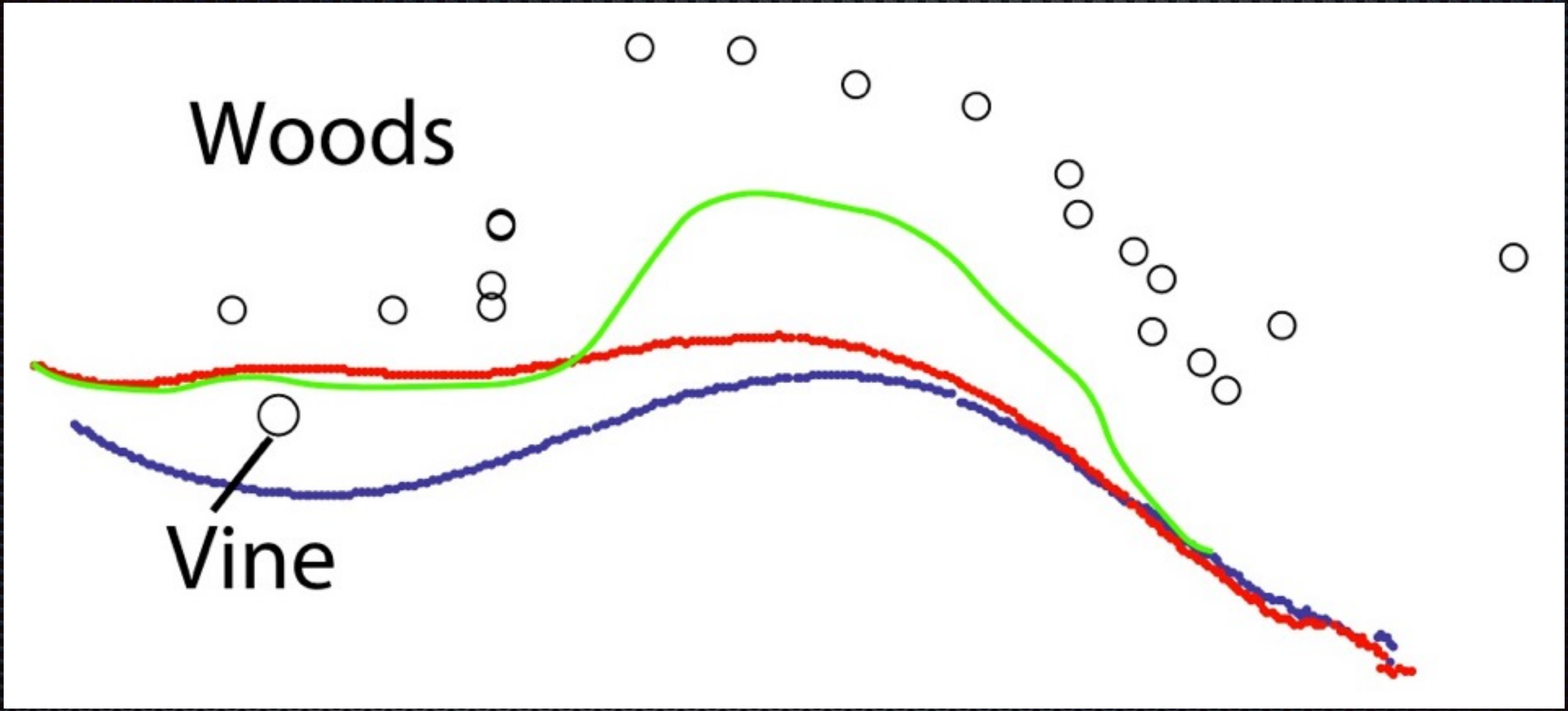
254 *M. velifer* trajectories statistics of the main subgroups



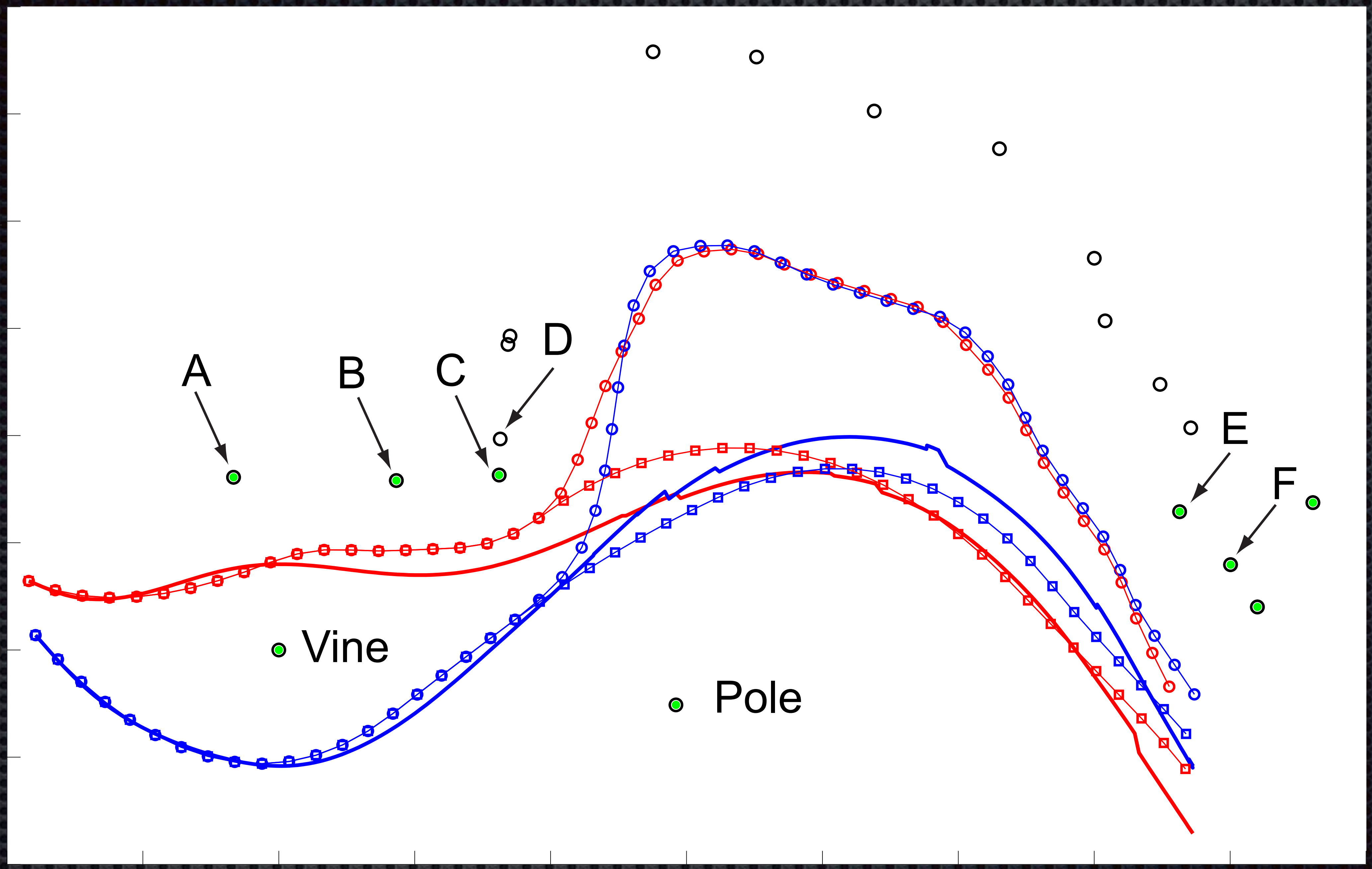
254 *M. velifer* trajectories statistics of the main subgroups



Synthesizing typical bat trajectories

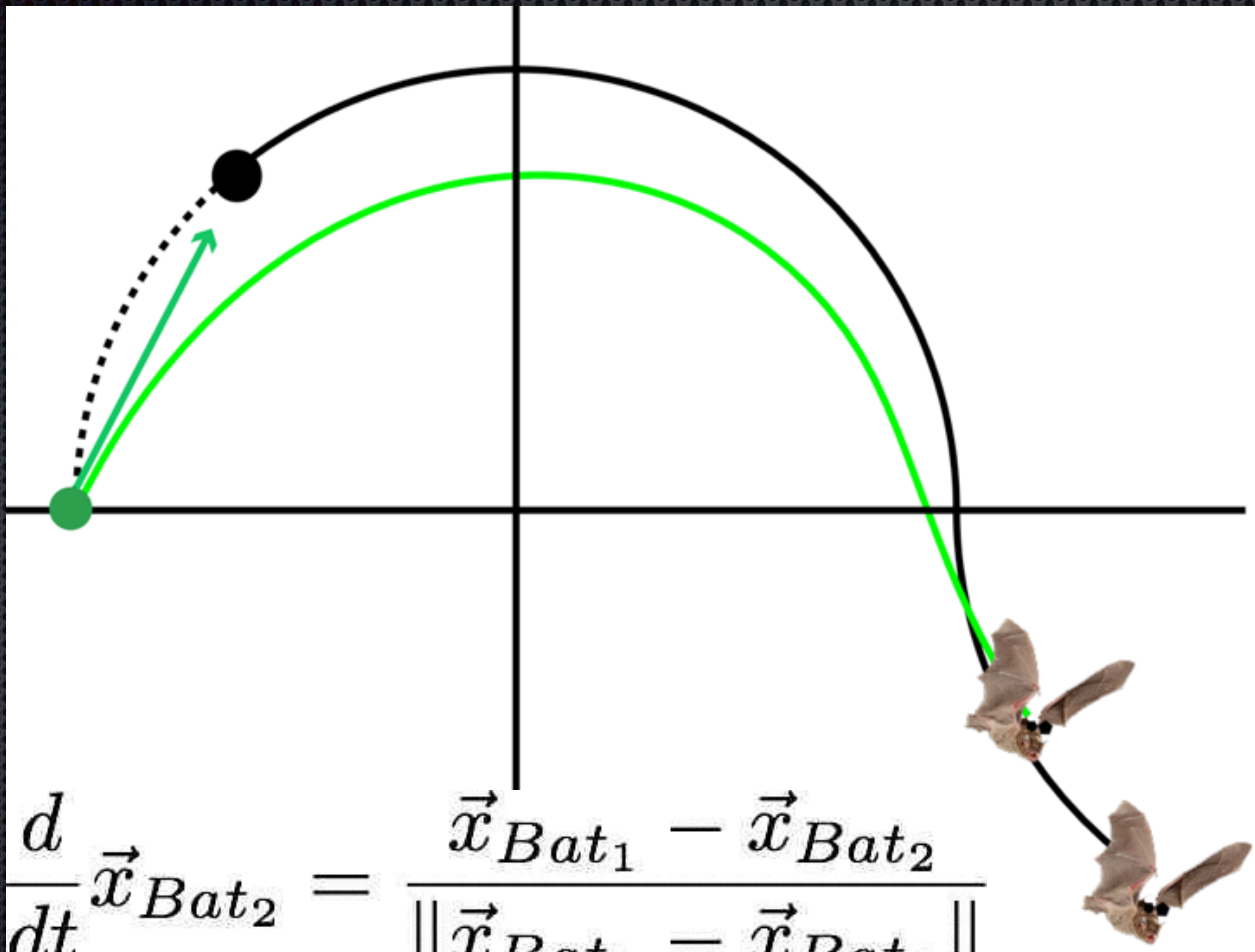


Comparing motion strategies



- solid lines–mean bat trajectories;
- curves with circles–synthesized trajectories based on forest cue strategy;
- curves with squares–synthesized trajectories based on integrated strategy.

Learning from the motions of others:



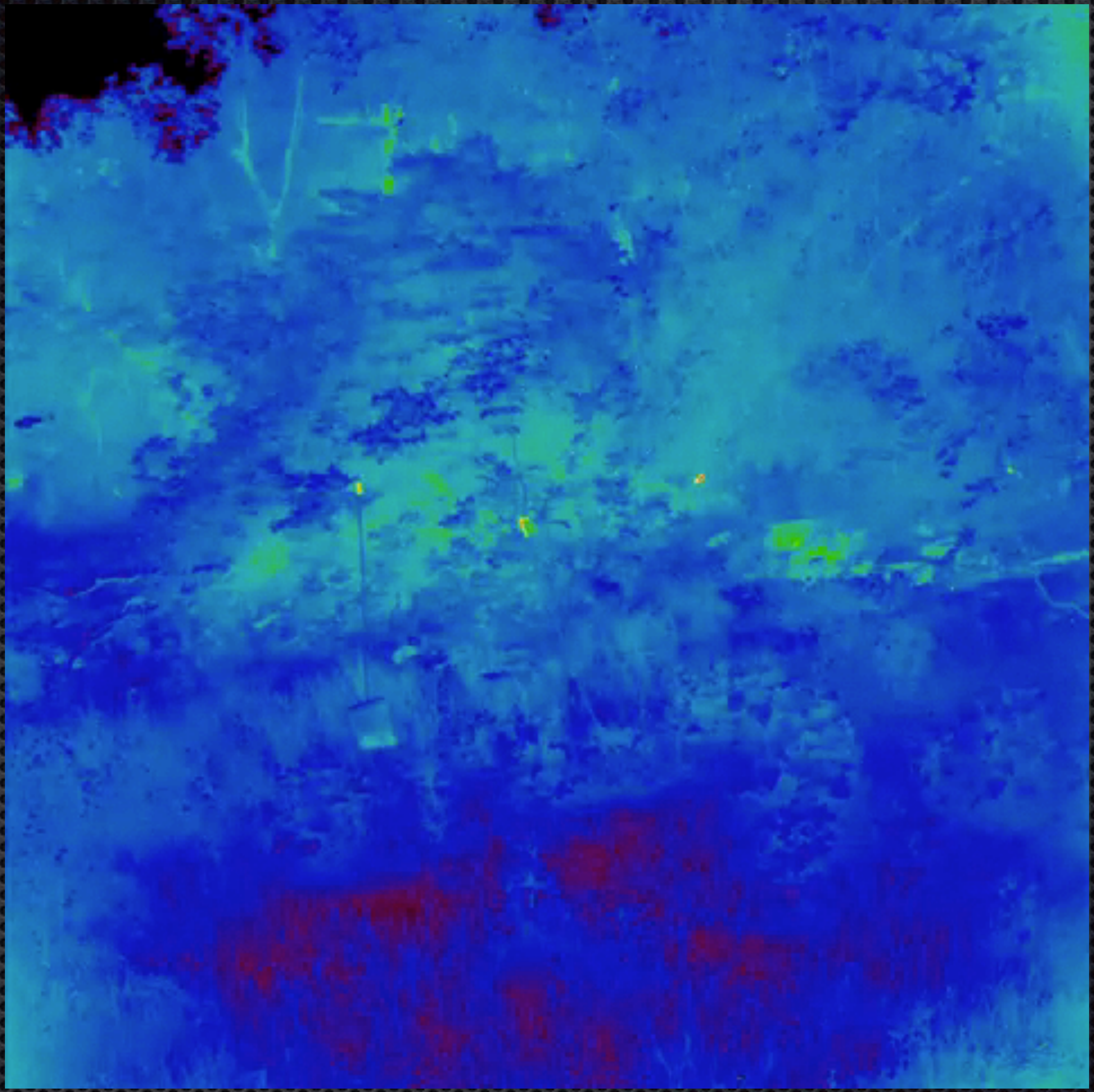
$$\frac{d}{dt}\vec{x}_{Bat_2} = \frac{\vec{x}_{Bat_1} - \vec{x}_{Bat_2}}{\left\|\vec{x}_{Bat_1} - \vec{x}_{Bat_2}\right\|}$$

Open questions (2012):

- Are the bats relying solely on optical flow?
- Why do some bats prefer the shorter route?
- Are shorter paths the result of learning and spatial memory?
- Are shorter paths the result of leader-follower kinematics?
- Can we disentangle the bats' use of echolocation and vision?
- How do these results change when the feedback models utilize higher multiplicities of features?

The rest may need to be rearranged.

Learning from the motions of others:

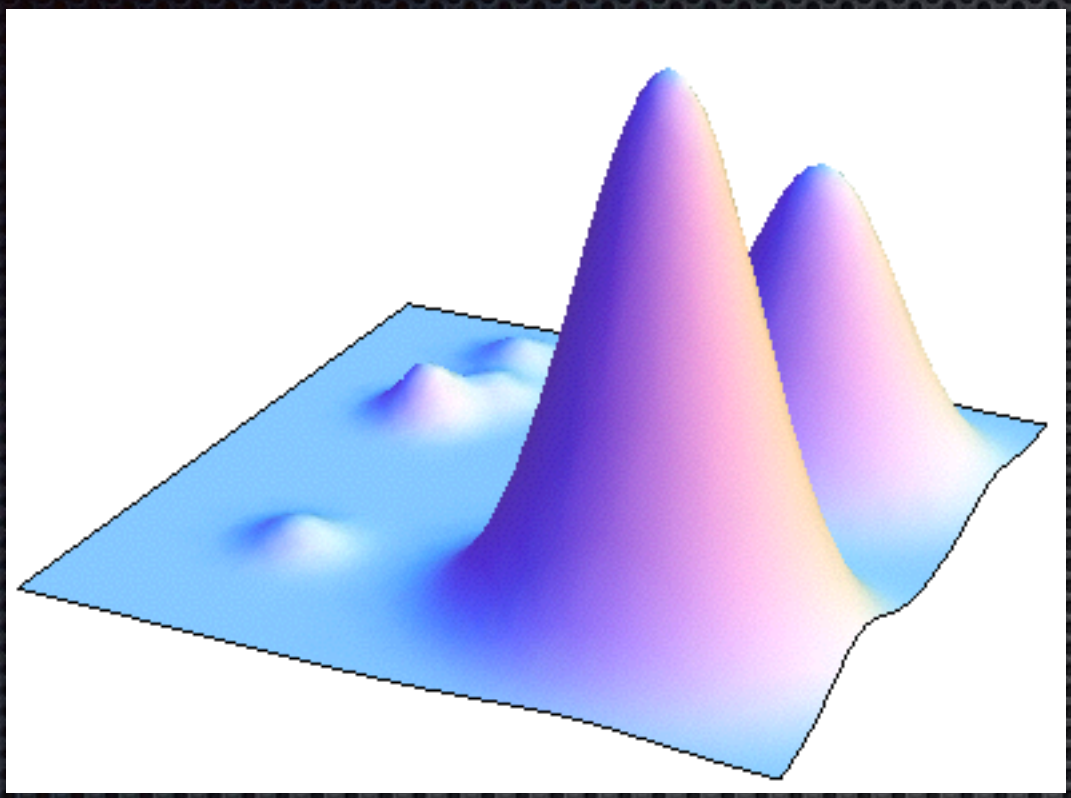


Collective behavior in sparse swarms

Laboratory experiments with optical flow sensing

More info: http://arxiv.org/abs/1203.2816

Features, textures, and noise - is there an entropy sweet spot?



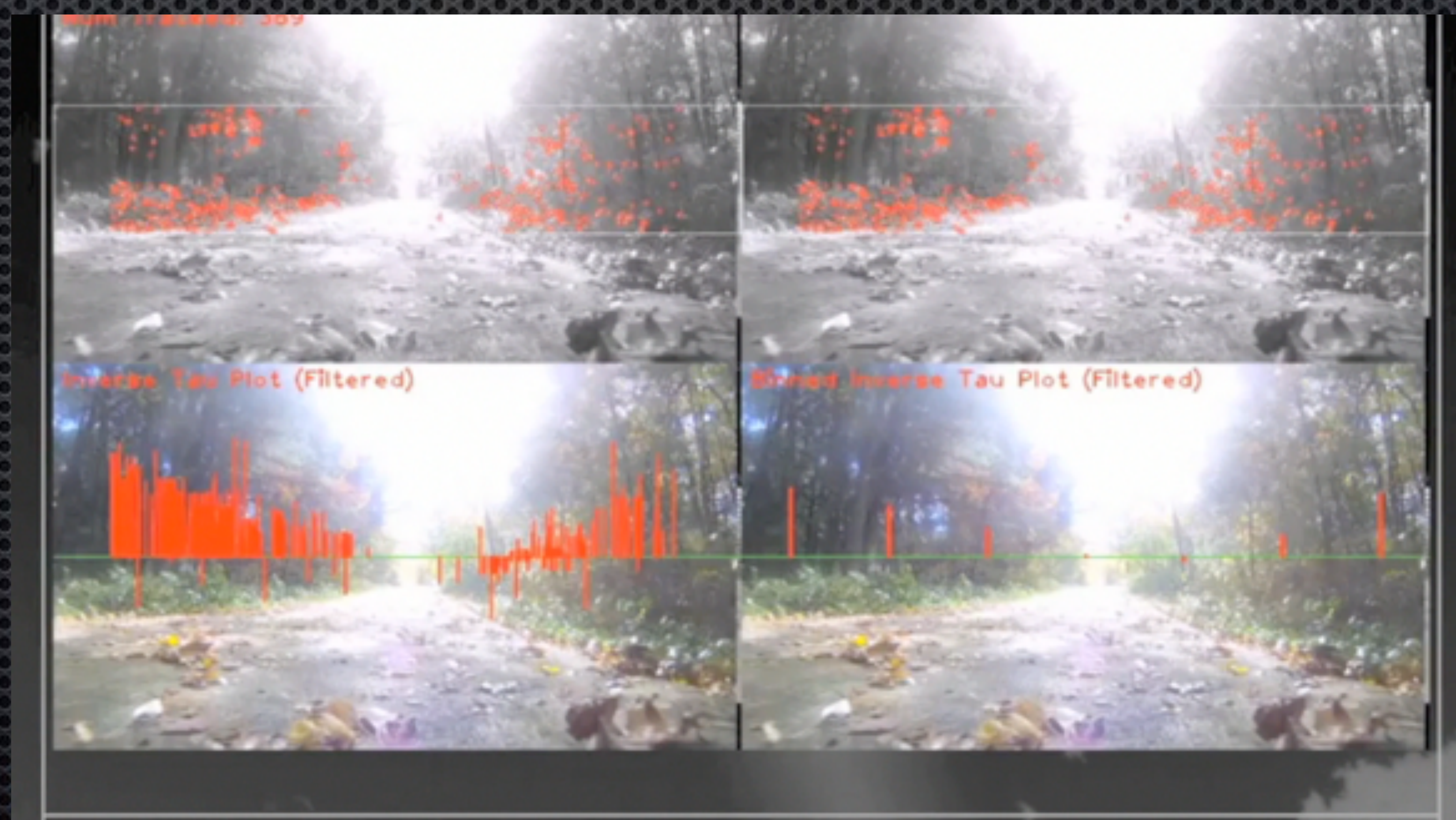
How can we quantify feature *significance*?

Too much detail ⇒ sensory overload.

There are entropy gradients in every environment.

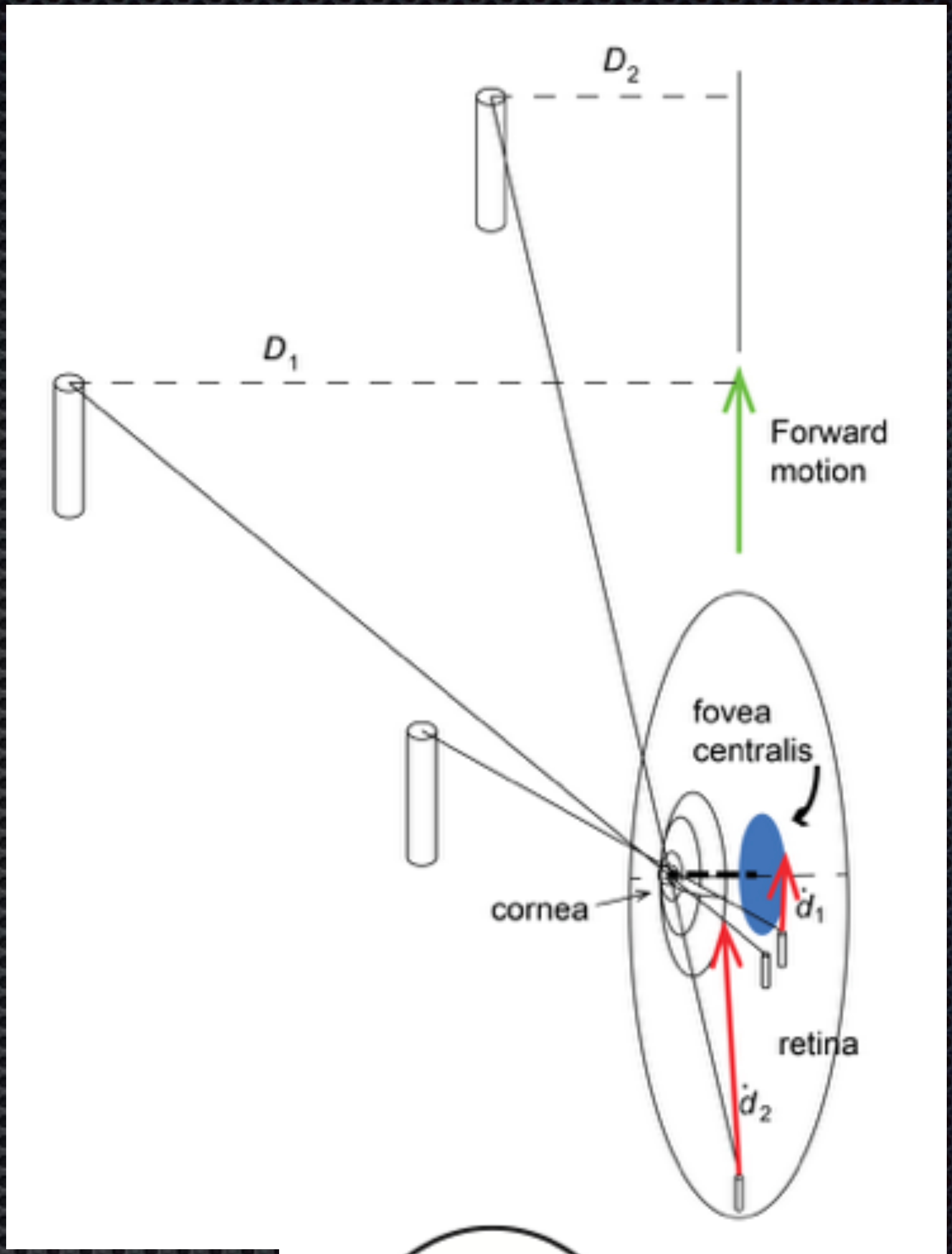
What remains to be done:

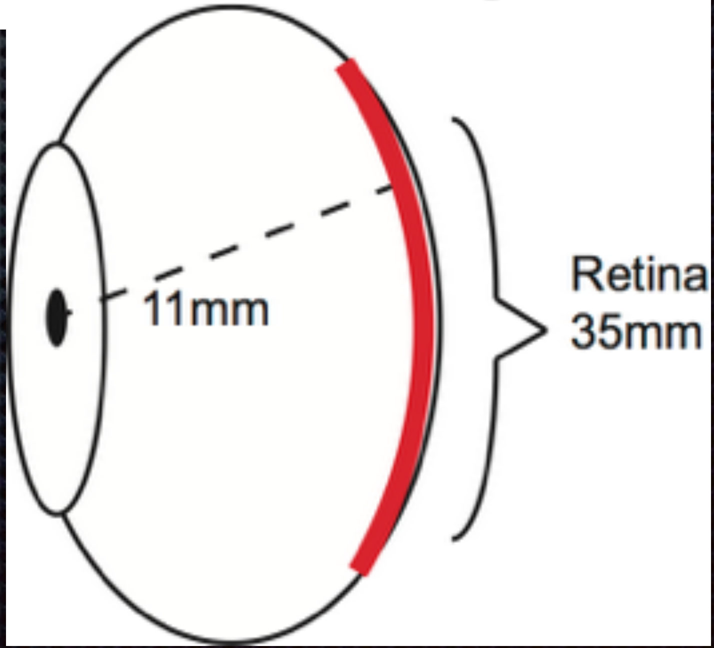
- Introduce environmental features that the bats will need to react to; understand the role of *learning and spatial memory*;
- Bring acoustic sensors to the field to make synchronized recordings of echolocation;
- Understand optical flow feedback using feature networks. (Put *SURF, BRISK, FREAK,* etc. into feedback loops.)



Thoughts on feature saliency

- Optical flow algorithms depend key point associations between video frames.
- Key point associations between frames becomes difficult if the key point image moves a large amount between frames.
- Key point images associated to nearby environmental features have high retinal velocity.





Thoughts on feature saliency

The velocity of image points $\dot{d}_i$ on the retina is inversely proportional to how close a straight line trajectory will pass the feature.

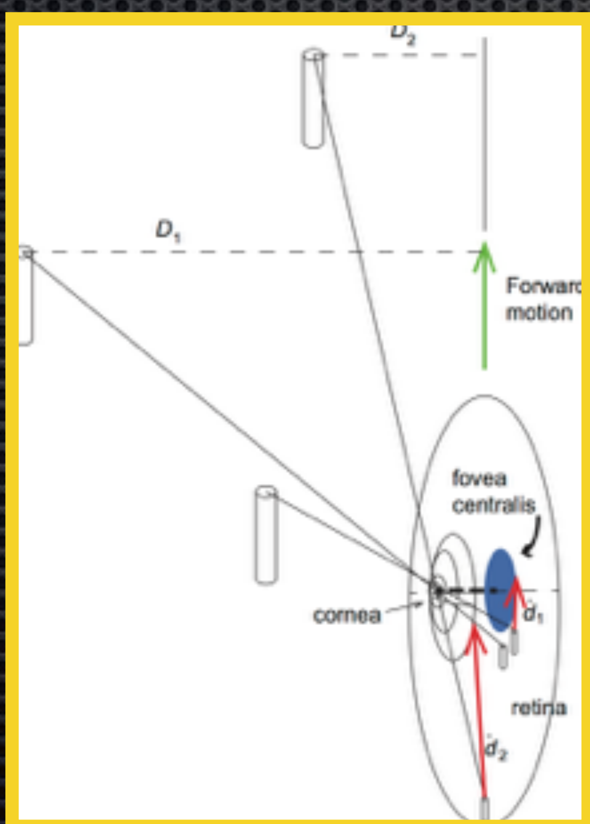
Simple geometry:

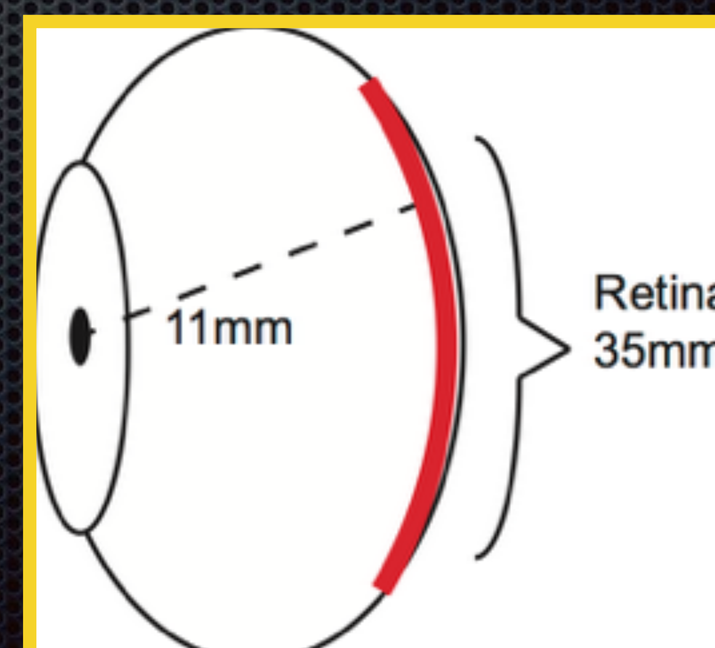
$$\frac{f}{\dot{d}} \sim \frac{D}{v}$$

For *M. velifer*:

$v = 10\,m/s$, $f = 11\,mm$ (in appropriate scale), and we assume $\dot{d} = 35mm/s$.

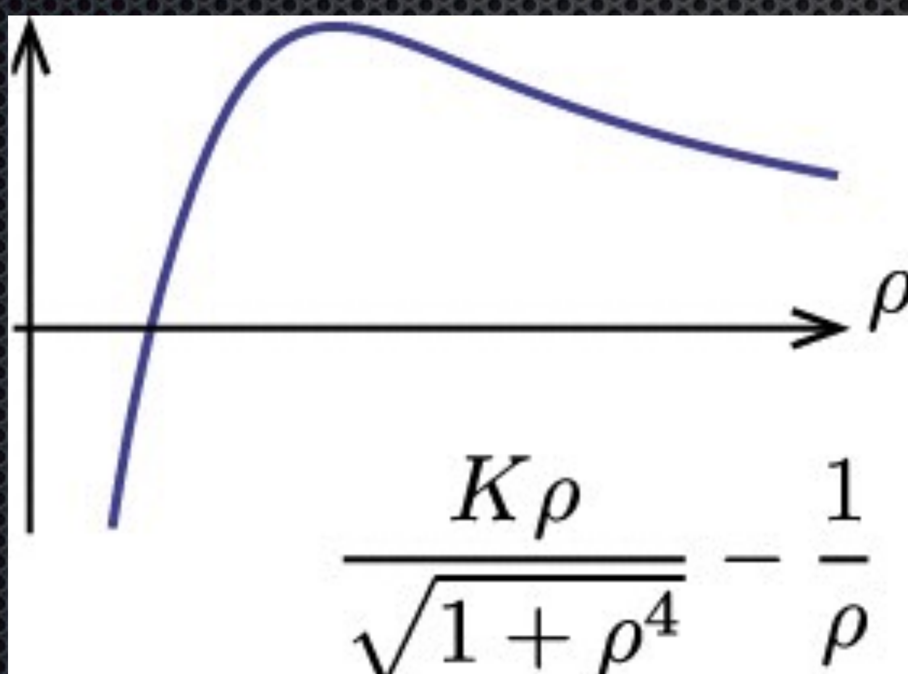
$\Rightarrow D \sim 3\,m$

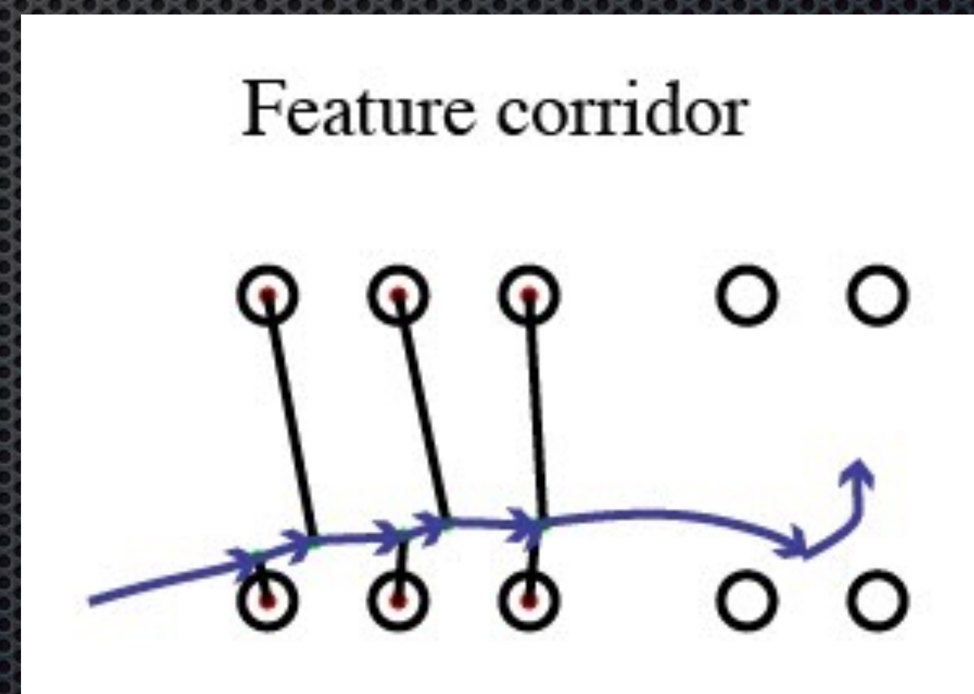




Navigating through feature networks:

$$\begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} = \sum_{k \in \mathcal{A}(t)} \left(\frac{K}{\sqrt{((x-x_k)^2+(y-y_k)^2)^2+1}} - \frac{1}{(x-x_k)^2+(y-y_k)^2} \right) \begin{pmatrix} x - x_k \\ y - y_k \end{pmatrix}$$





Control over feature-actuator networks with channel intermittency:

$$\dot{x} = Ax + Bu$$

$$y = Cx$$

$$x \in \mathbb{R}^n, \ u \in \mathbb{R}^m, \ y \in \mathbb{R}^q$$

$$m > 1, \ q > 1$$

Channels are available intermittently.

This is kept track of by an $m \times m$ diagonal matrix $M(t)$ and a $q \times q$ diagonal matrix $K(t)$ with 1's and 0's on the diagonal.

Networked control with channel intermittency:

$$\dot{x} = Ax + BM(t)u$$

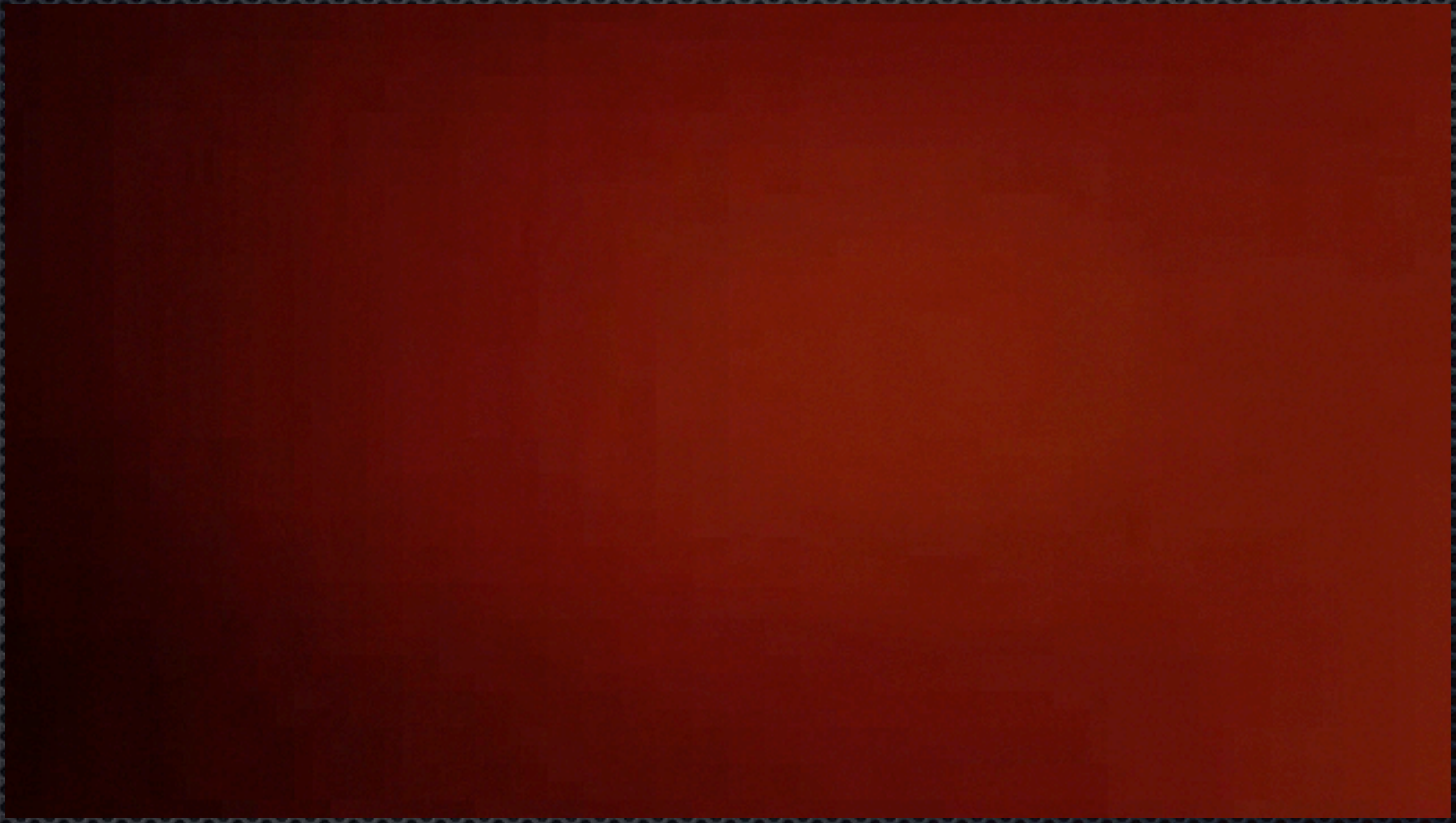
$$y = K(t)Cx$$

$$x \in \mathbb{R}^n, \ u \in \mathbb{R}^m, \ y \in \mathbb{R}^q$$

$$m > 1, \ q > 1$$

Contributions to this problem:
Zhang & Hristu, Automatica, 2006, Yu and Andersson, CDC , 2013, JB and Kong, CDC (?), 2014 & arXiv.org

Animal-inspired autonomous flight in the news



Summary — and what's next

- Observed flight behaviors may be reactions to visual cues.
- Animals have affinity for information-rich flight arenas.
- How are sensory inputs blended with spatial memories?