Bat swarms and the role of active sensing: models and experimental framework

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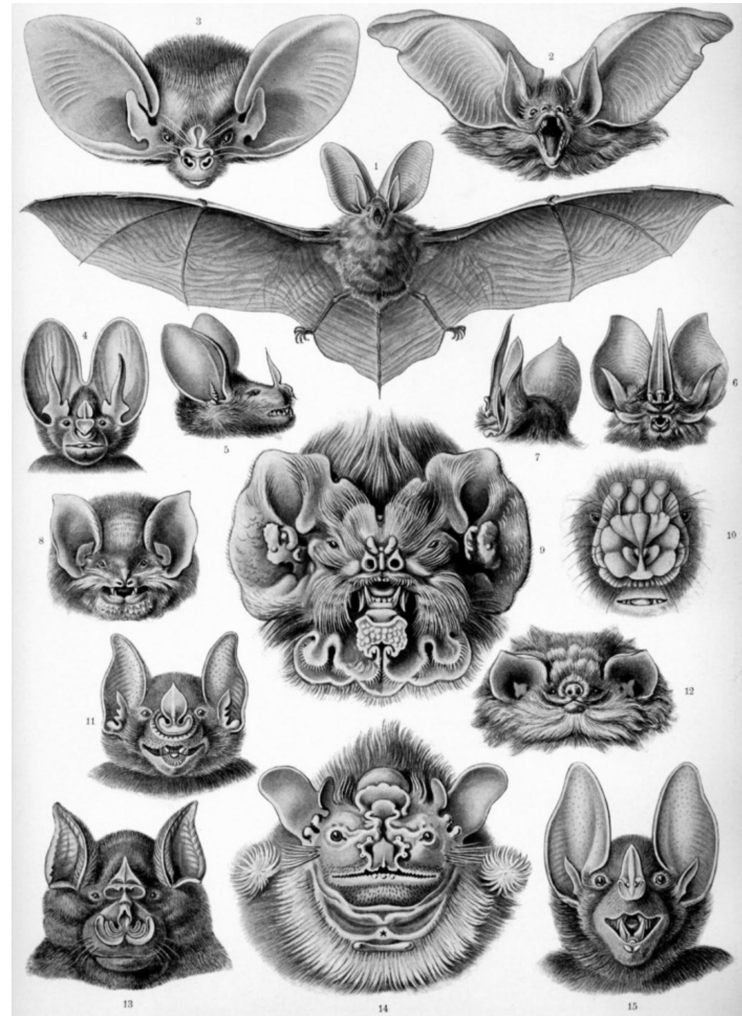
Collective behavior

- **Collective behavior:** complex pattern in an animal group emerging from simple rules based on local interactions
- **Good for:** protection from predation, mating, foraging…
- **Bad for:** competition for resources, jamming…

Bats

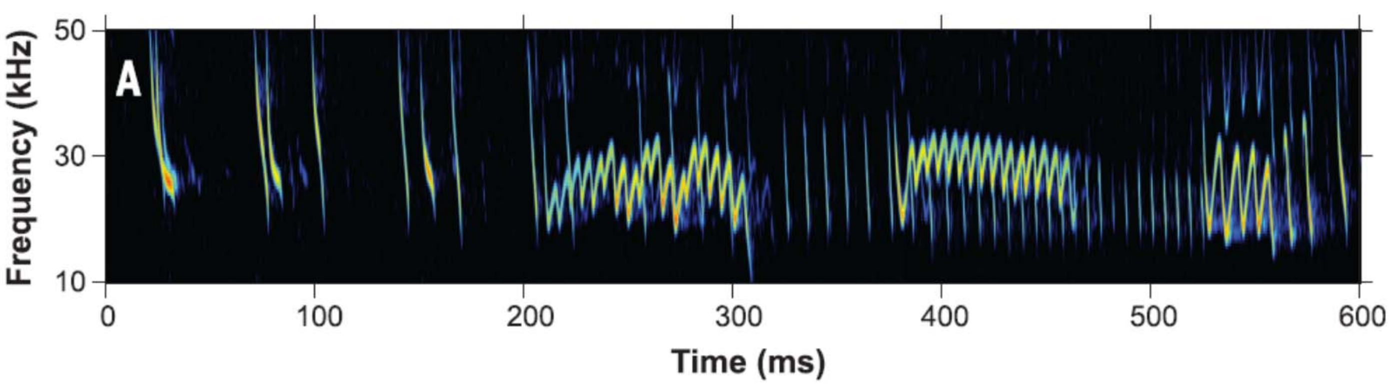
- Suborder Microchiroptera
- Use echolocation
- Live in colonies
- Many insectivorous species



(Chiroptera plate from Ernst Haeckel's Kunstformen der Natur, 1904)

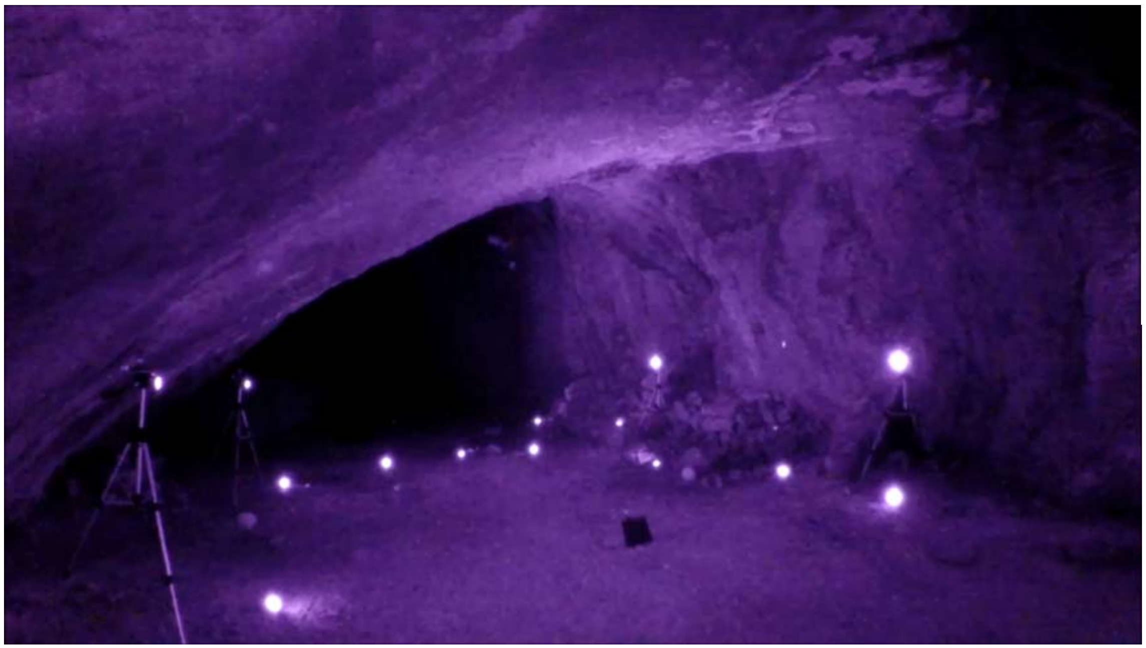
Bat echolocation strategies

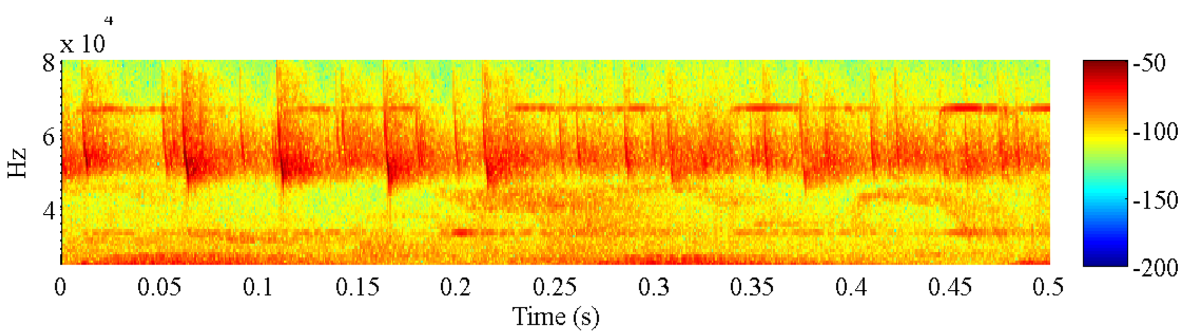
- Frequency modulation
  - N. Ulanovsky et al., 2004. "Dynamics of jamming avoidance in echolocating bats." Proc of the Royal Society of London B 271(1547), pp. 1467-1475
  - M. E. Bates et al., 2008. "Jamming avoidance response of big brown bats in target detection." Journal of Experimental Biology 211(1), p. 106-113
- Vocalization cessation
  - C. Chiu, W. Xian, and C. F. Moss, 2008. "Flying in silence: Echolocating bats cease vocalizing to avoid sonar jamming." PNAS 105(35), pp. 13116–13121
- Offensive jamming for hunting
  - A. J. Corcoran and W. E. Conner, 2014. "Bats jamming bats: Food competition through sonar interference." Science 346(6210), pp. 745-747



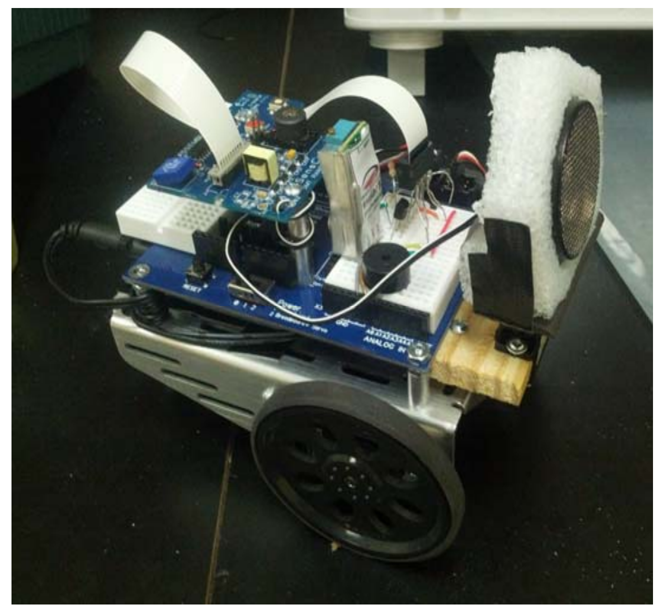
Long term goals

Long-term goal: Develop a multi-agent system with active sensors capable of strategically coupled communication and sensing





Applications:
Cooperative sensing in vehicle teams, animal-robot interactions



This talk

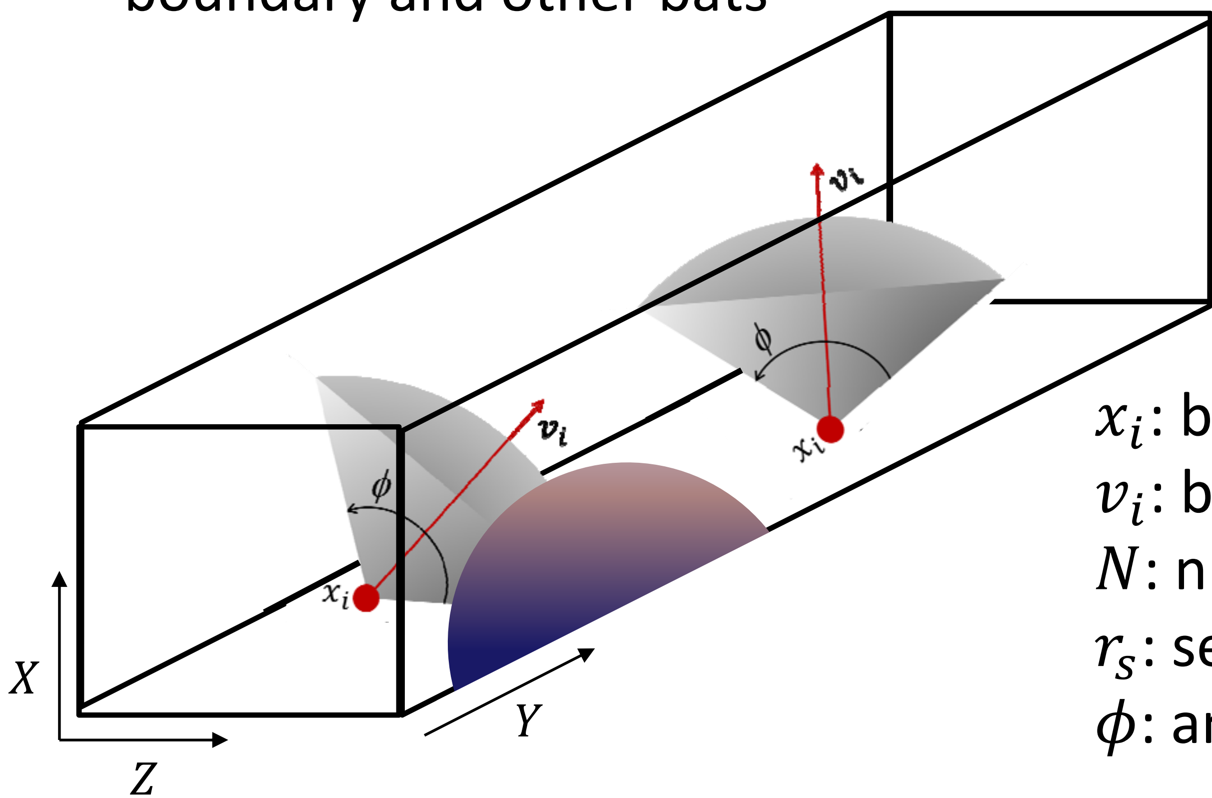
1. Feasibility of a bat-inspired network that can "passively" collaborate to avoid collisions:
   - **Agent-based model and simulation**

2. Two aspects of the future robotic bat swarm:
   - Experimental setup for capturing data from wild bat swarms
   - Network-based modeling to design interactions

3. Where we go next: robots!

Feasibility study: Agent-based model of collision avoidance

- Bats are self-propelled particles with constant speed
- 3D duct with periodic boundaries and discrete time
- Collision avoidance using conical sensing space, echoes from boundary and other bats



x_i: bat i's position vector
v_i: bat i's velocity vector
N: number of bats
r_s: sensing range
ϕ: angular sensing range

Modeling (1)

Position update: $x_i(t + \Delta t) = x_i(t) + v_i(t + \Delta t)\Delta t,$
$i = 1,2, \dots, N$

Velocity update :

$$v_i(t + \Delta t) = \alpha v_i(t) - \beta \left[\frac{\sum_{j \in E} e_j(t)}{\left\| \sum_{j \in E} e_j(t) \right\|} + \frac{\sum_{j \in \tilde{E}} \tilde{e}_j(t)}{\left\| \sum_{j \in \tilde{E}} \tilde{e}_j(t) \right\|} \right] + \gamma \sigma + \omega$$

α, β, γ: weighting parameters

e: position of echoes bat *i*'s senses as too close using its own echolocation pulse (set of these echoes is E)

$\tilde{e}$: position of echoes bat *i*'s senses as too close using peers' echolocation pulse (set of these echoes is $\tilde{E}$)

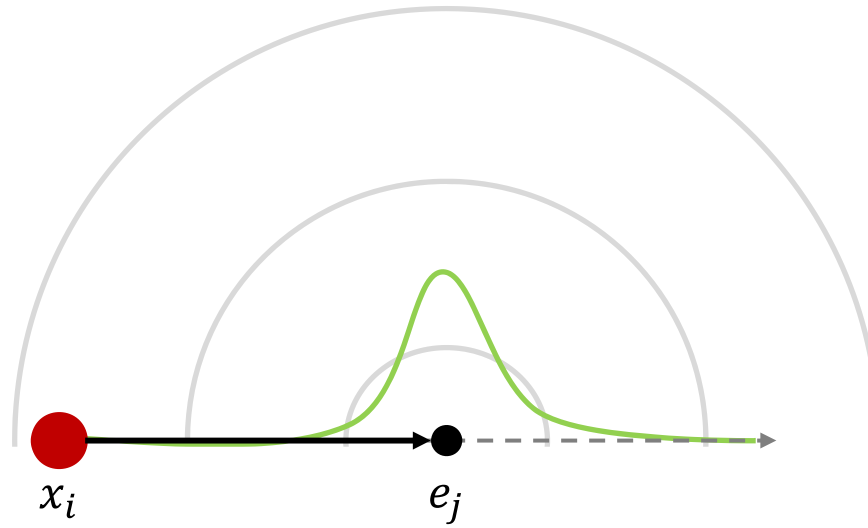
σ: unit vector in the positive y direction

ω: random vector with Gaussian distribution for length, uniform for direction

Modeling (2)

Eavesdropping:

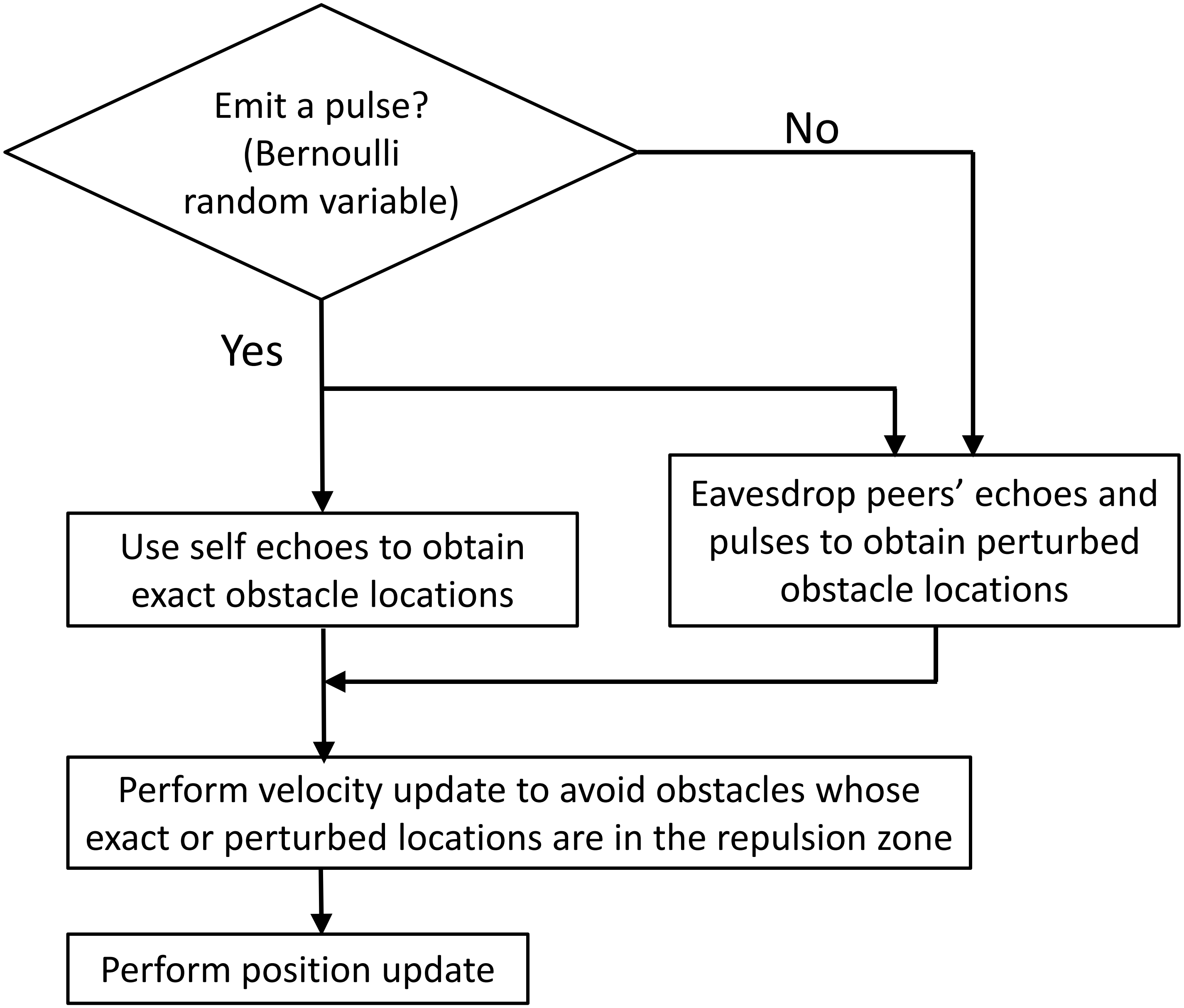
- Echoes perceived from own echolocation pulse give true position of echo's center
- Echoes received from peers perturbed by Gaussian noise



Ceasing echolocation:

- Chiu et al., 2008. "Flying in silence: echolocating bats cease vocalizing to avoid sonar jamming". *PNAS*, 105(35), p. 13116
- Probability to cease emitting echolocating pulses and only use peers' echoes passively
  - $p = 0$: Never emit pulse at time step after hearing peers' echoes
  - $p = 1$: Always emit pulses regardless of prior information

Model flowchart



Metrics

- Mean number of collisions over sim, individuals: *c*
  - May be compared to collisions for sim with no eavesdropping: c’
- Balance between collisions and energy use:

$$s_1 = c + \alpha_1 N p$$

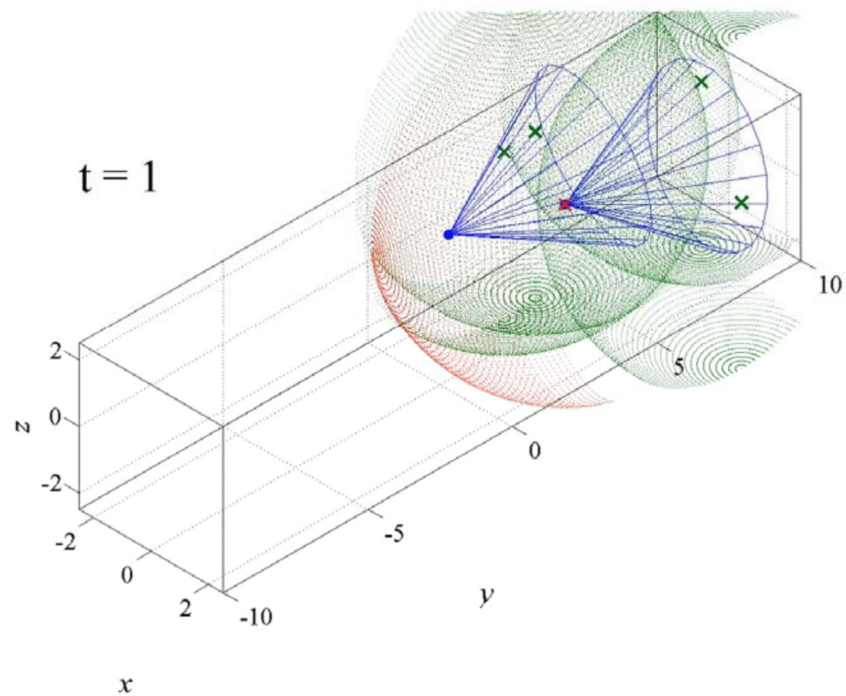
Number of collisions averaged over time and individuals

Weight to balance orders of magnitude

Mean number of echolocation pulses over group, ~ sensing energy, jamming, etc.

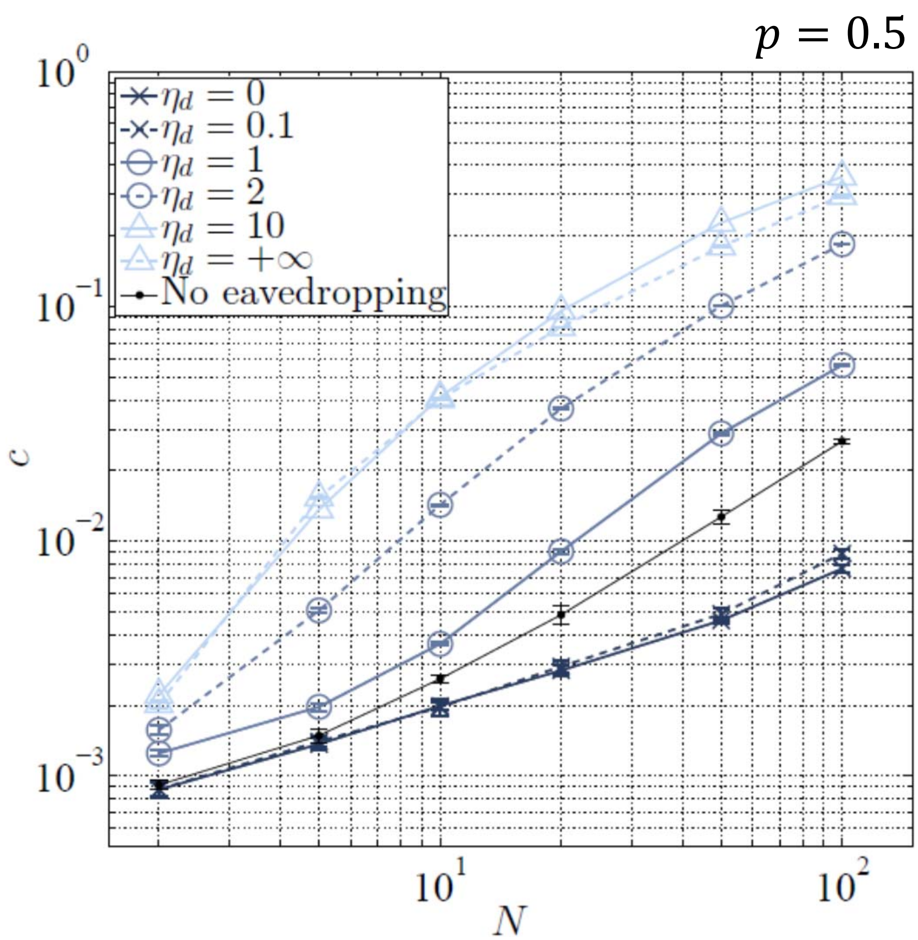
Simulations

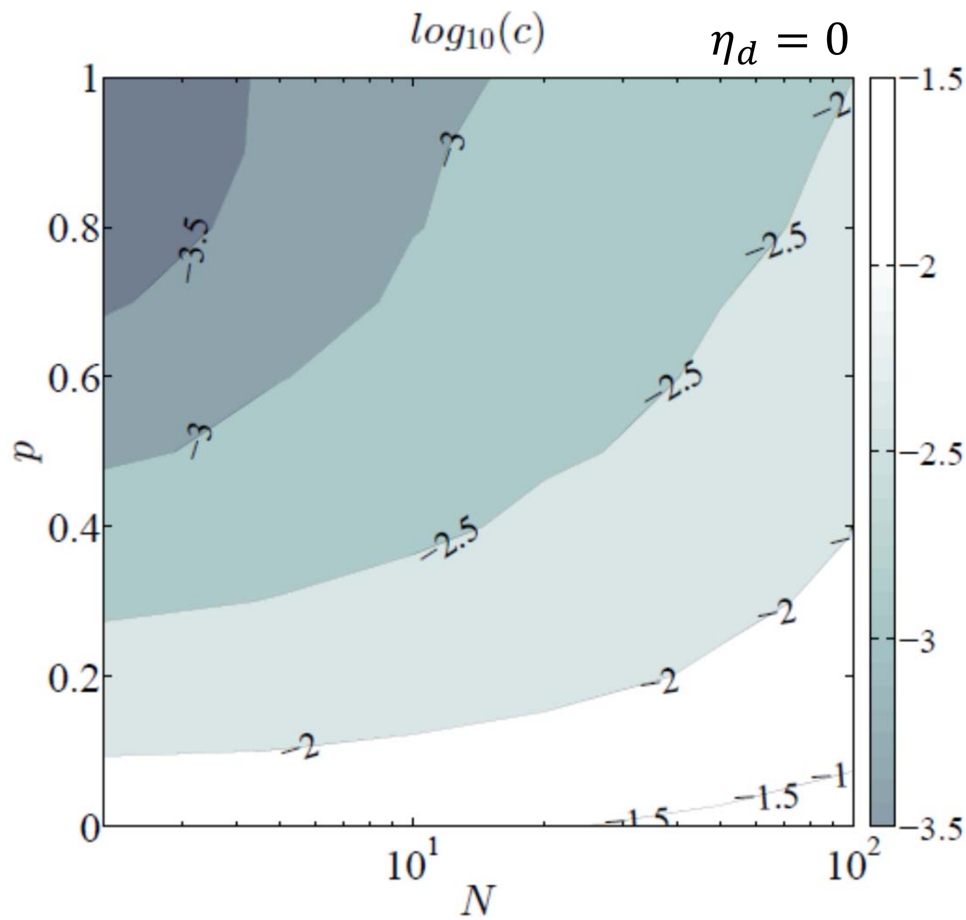
- Parameter values inspired by big brown bats, *Eptesicus fuscus*
- Ten replicates with each replicate as 3000 time steps Domain dimensions: 20m x 5m x 5m
- Bat sensing geometry r_s=5m, ϕ=60°
- Group sizes: $N = \{5, 10, 20, 50, 100\}$
- Measurement noise: $\eta_d = [10^{-3}, 10^5]$
- Emission probabilities: $p = \{0, 0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1\}$



Simulation results: Collisions

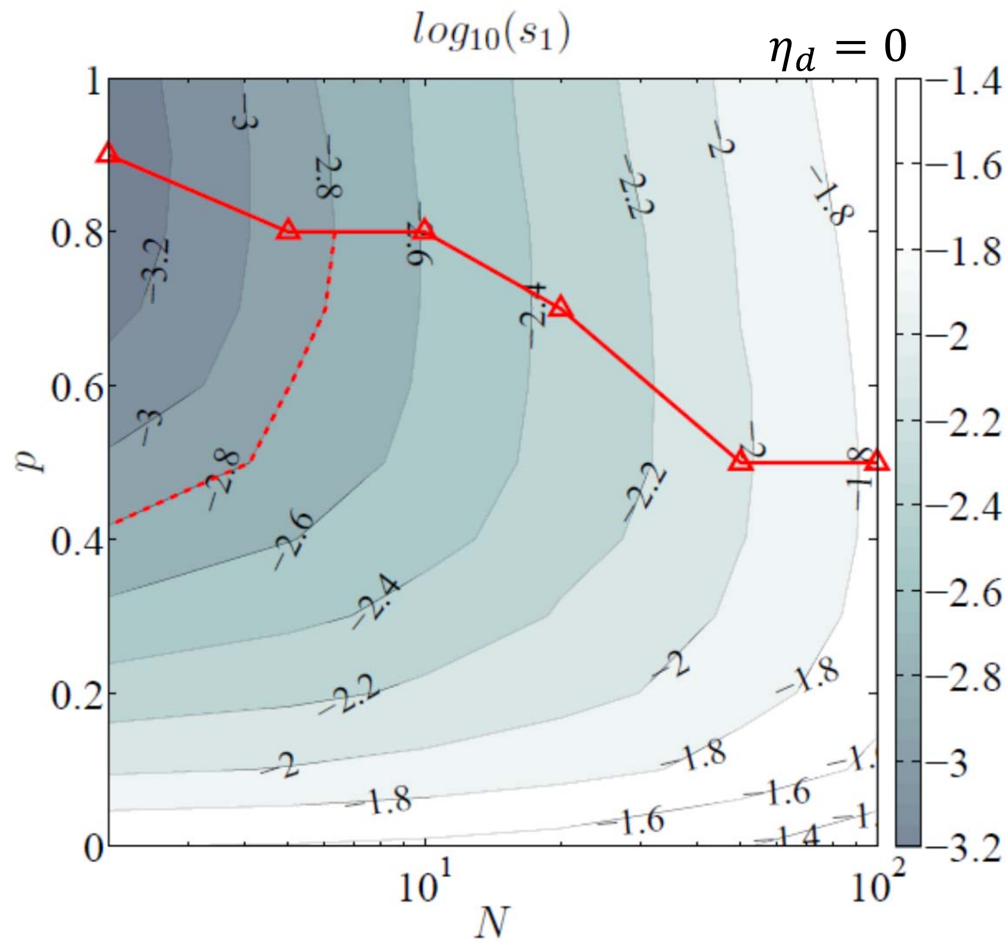
- Small measurement noise > no eavesdropping
- Collisions increase as *N* increases, *p* decreases





Simulation results: Cost

- *p* corresponding to minimum cost decreases as *N* increases
- Big idea:
  - Small measurement noise -> avoid collisions better by eavesdropping than not
  - Total energy can be saved and potential jamming avoided by echolocating less



There are cases when communicating over sensing channels may be advantageous

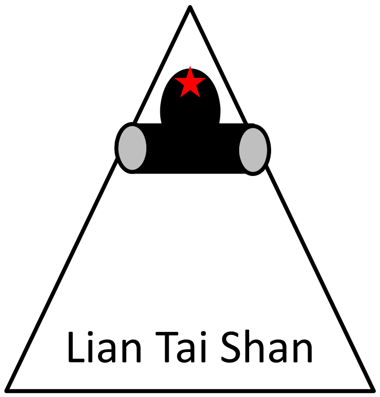
This talk

1. Feasibility of a bat-inspired network that can "passively" collaborate to avoid collisions:
   - Agent-based model and simulation

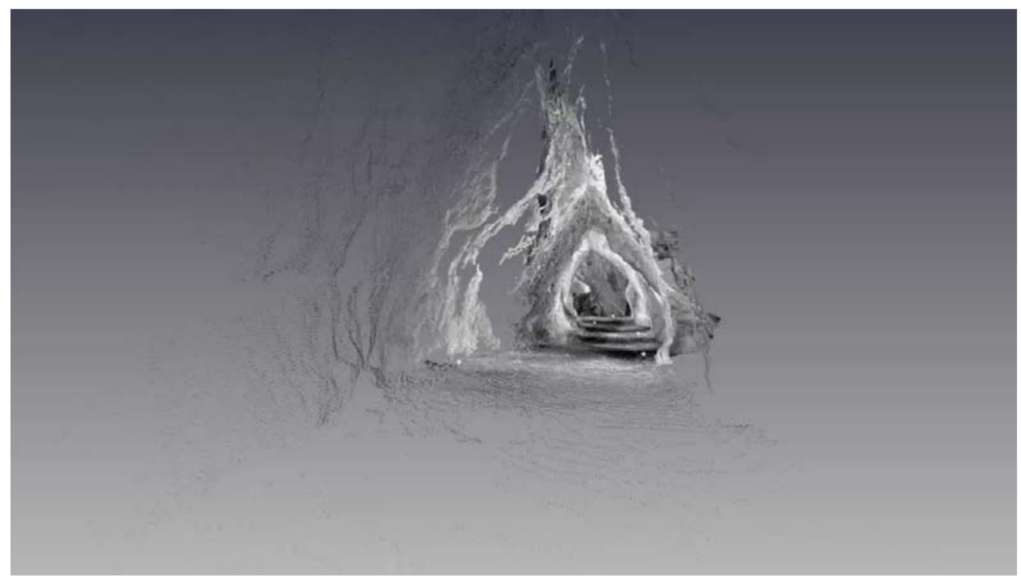
2. Two aspects of the future robotic bat swarm:
   - **Experimental setup for capturing data from wild bat swarms**
   - Network-based modeling to design interactions

3. Where we go next: robots!

Experiments with wild bat swarms in Shandong Province, China



Research question: is information shared in pairs flying together? Who is following/leading?



Field equipment

Video system

Audio system

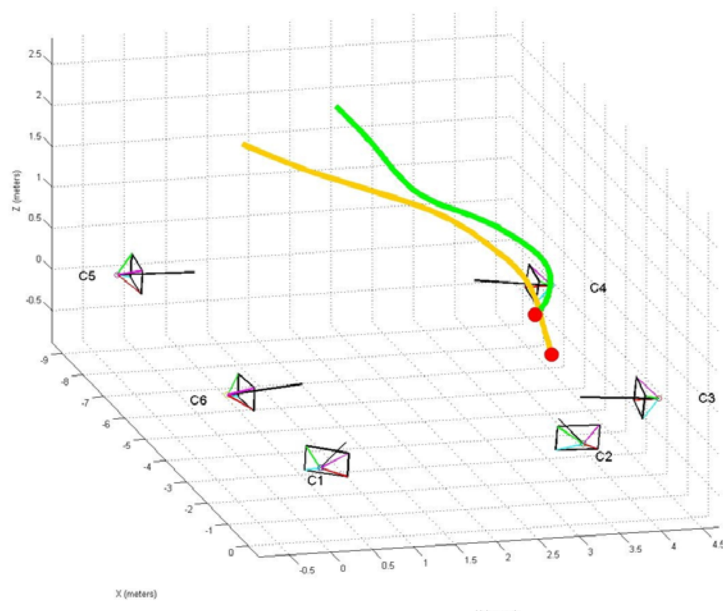
- 6 GoPro cameras modified to have IR-sensitive lenses
- 15 IR illuminators
- Tablet with WIFI

Experimental setup

Video data

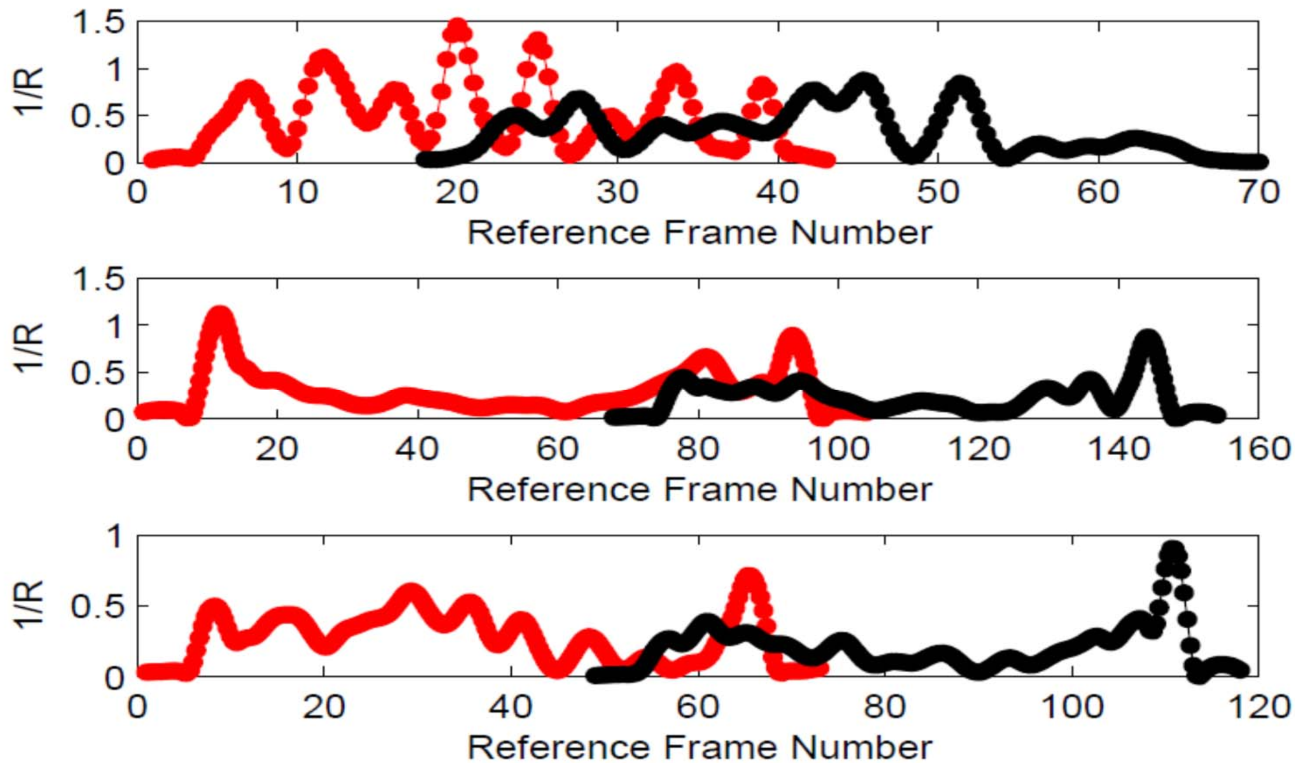
Data analysis

- Measure intrinsic camera parameters, input into calibration code
- Extract extrinsic camera parameters from calibration code with laser pointer test
- Track bat positions in all 6 camera views
- Compute 3D bat position using a least squares minimization scheme



Transfer entropy analysis

- Possible variables of interest: curvature of flight path, speed,…
- Information theoretic approach: Transfer entropy



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Coordination in bat swarms

For example:

- Coordinated flight
- Nightly emergence timing
- Roost selection

http://www.tripadvisor.com/Attraction_Review-g30196-d106309-Reviews-Congress_Avenue_Bridge_Austin_Bats-Austin_Texas.html

Consensus protocols

Consensus protocols are distributed algorithms executed by a group of agents interacting to agree on common quantity of interest

A discrete-time protocol for N agents can be written as the linear system:

$$x(k+1) = W(k)x(k)$$

From conspecific agents

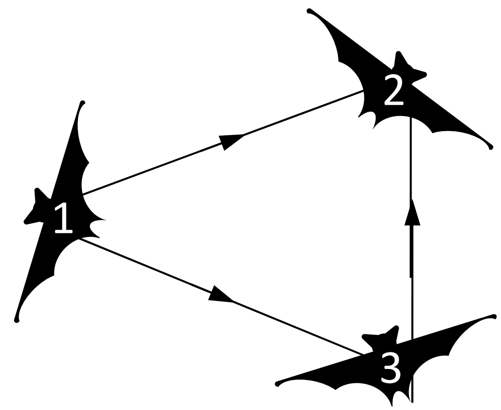
with

- $W(k)1_N = 1_N$ for all k and typically use $\boxed{W(k) = I_N - \epsilon L(k)}$
- $x(k) \in R^N$ is the state vector
- $k > 0$ is the time index

Background on networks

Networks can be described equivalently as graphs and matrices

- Vertices *i=1,.., N*
- Directed edge *e*=(*i, j*) denotes *j* is a neighbor of *i*
- Out- and in-degree of a vertex
- Characteristic matrices: *L = D - A*



Directed network with *N*=3 and edges (1,2), (1,3), and (3,2)

Degree matrix

$$D = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Adjacency matrix

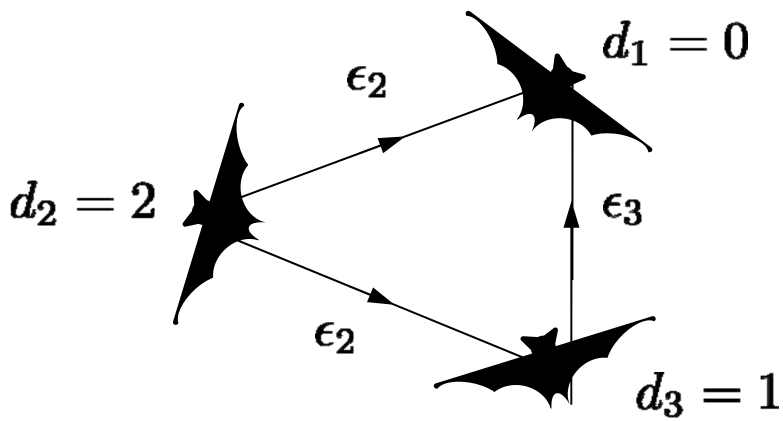
$$A = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

Laplacian matrix

$$L = \begin{bmatrix} 2 & -1 & -1 \\ 0 & 0 & 0 \\ 0 & -1 & 1 \end{bmatrix}$$

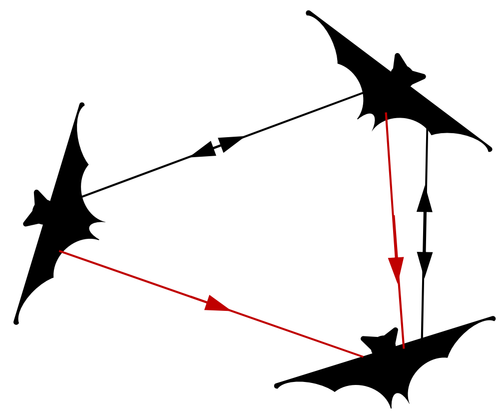
Conspecific model

- Homogeneous individuals from Abaid, Igel, and Porfiri 2012
- Draw traits from bivariate distribution: $g_{D,\mathcal{E}}(d,\epsilon)$
- Random variable D quantifies the cardinality of neighbor set
- Random variable $\mathcal{E}$ quantifies each agents' averaging weight or "stubbornness"
- $d_1, d_2,$ and d_3 are realizations of D
- $\epsilon_1, \epsilon_2,$ and ϵ_3 are realizations of $\mathcal{E}$
- Weighted Laplacian matrix: $M = \text{diag}([\epsilon_1, \epsilon_2, \epsilon_3])L$



Modeling eavesdropping versus jamming: Collaborative and antagonistic interactions

- Collaborative pdf: $g_{\mathcal{D}_1,\mathcal{E}_1}(d_1,\epsilon_1)$
- Antagonistic pdf: $g_{\mathcal{D}_2,\mathcal{E}_2}(d_2,\epsilon_2)$
- $M(k) = M_1(k) - M_2(k)$



- Example:

$$M_1(k) = \begin{bmatrix} 0.2 & -0.2 & 0 \\ -0.1 & 0.2 & -0.1 \\ 0 & -0.3 & 0.3 \end{bmatrix} \quad M_2(k) = \begin{bmatrix} 0.1 & 0 & -0.1 \\ 0 & 0.2 & -0.2 \\ 0 & 0 & 0 \end{bmatrix}$$

Back to consensus protocols

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A discrete-time protocol for N agents can be written as the linear system:

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- $W(k)1_N = 1_N$ for all k and typically use $W(k) = I_N - M(k)$
- $x(k) \in R^N$ is the state vector
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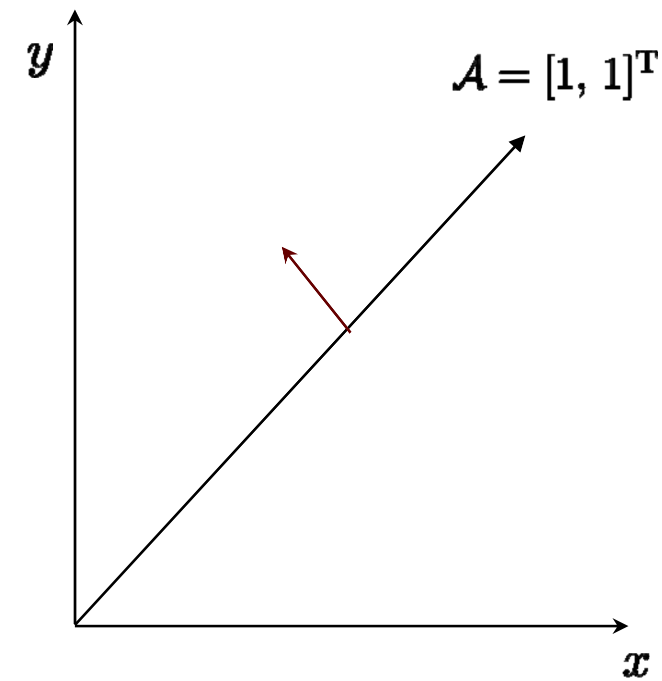
Convergence to consensus (1)

Assess consensus through disagreement dynamics [Porfiri 2007]

- Consensus protocol is
$$x(k+1) = W(k)x(k)$$
- Disagreement variable is $\xi(k)$
- Low-dimensional disagreement system is $\xi(k+1) = \widetilde{W}(k)\xi(k)$

Stability of disagreement is taken as the consentability of total dynamics



Convergence to consensus (2)

Measuring the disagreement:

- Mean square stability: $\lim_{k\to\infty} \mathbf{E}[\|\xi_k\|^2] = 0$ for all ξ_0
- Asymptotic convergence factor: $r_a = \sup_{\|\xi_0\|\neq 0} \lim_{k\to\infty} \left(\frac{\mathbf{E}[\|\xi_k\|^2]}{\|\xi_0\|^2} \right)^{1/k}$
- Necessary and sufficient condition for convergence:
  - closer to zero means faster convergence
  - $r_a > 1$ means no convergence
- Calculated from the spectral radius of a "second-moment matrix: $r_a(W) = \rho((R \otimes R)[W \otimes W])$ where $R = I_N - \frac{1}{N}\mathbf{1}_N\mathbf{1}_N^{\mathrm{T}}$

Projection onto $\mathrm{span}(\mathbf{1}_N \otimes \mathbf{1}_N)^{\perp}$

Convergence to consensus (3)

Expected properties of networks:

- State matrix is $W(k) = I_N - M(k)$, where $M(k)$ describes a sequence of IID random networks
- Find the second-moment matrix by counting realizations of M
- The second-moment matrix has at most four distinct eigenvalues and linearly independent eigenspaces, for which we can find closed forms

Main result:

The asymptotic convergence factor is

$$r_a = \left(1 - \frac{N\eta_1}{N-1}\right)^2 - \frac{N}{N-1}\left({\phi_1}^2 + {\psi_1}^2\right) + (\phi_2 + \psi_2) + (\phi_3 + \psi_3)$$

with

$$\phi_1 = \mathbf{E}[\mathcal{E}_1\mathcal{D}_1], \phi_2 = \mathbf{E}[{\mathcal{E}_1}^2{\mathcal{D}_1}^2],\ \phi_3 = \mathbf{E}[{\mathcal{E}_1}^2\mathcal{D}_1]$$

$$\psi_1 = \mathbf{E}[\mathcal{E}_2\mathcal{D}_2], \psi_2 = \mathbf{E}[{\mathcal{E}_2}^2{\mathcal{D}_2}^2],\ \psi_3 = \mathbf{E}[{\mathcal{E}_2}^2\mathcal{D}_2]$$

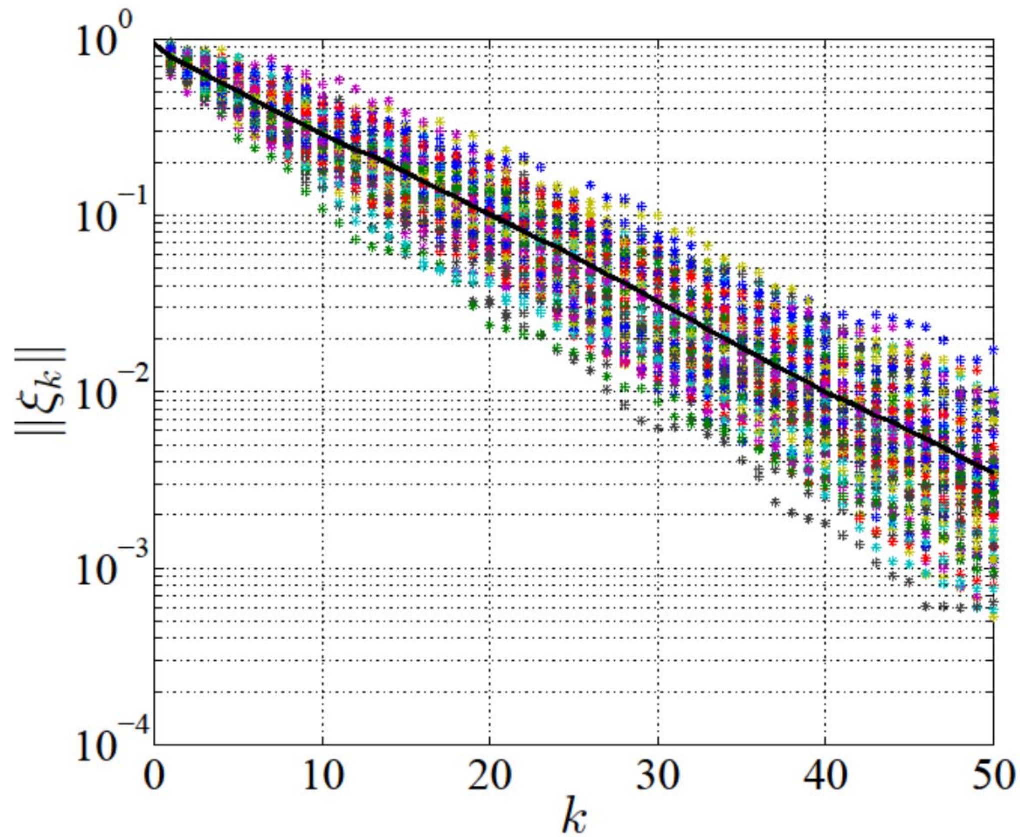
$$\eta_1 = \phi_1 - \psi_1$$

Numerical validation

We validate these results using Monte Carlo simulations with $N = 10$

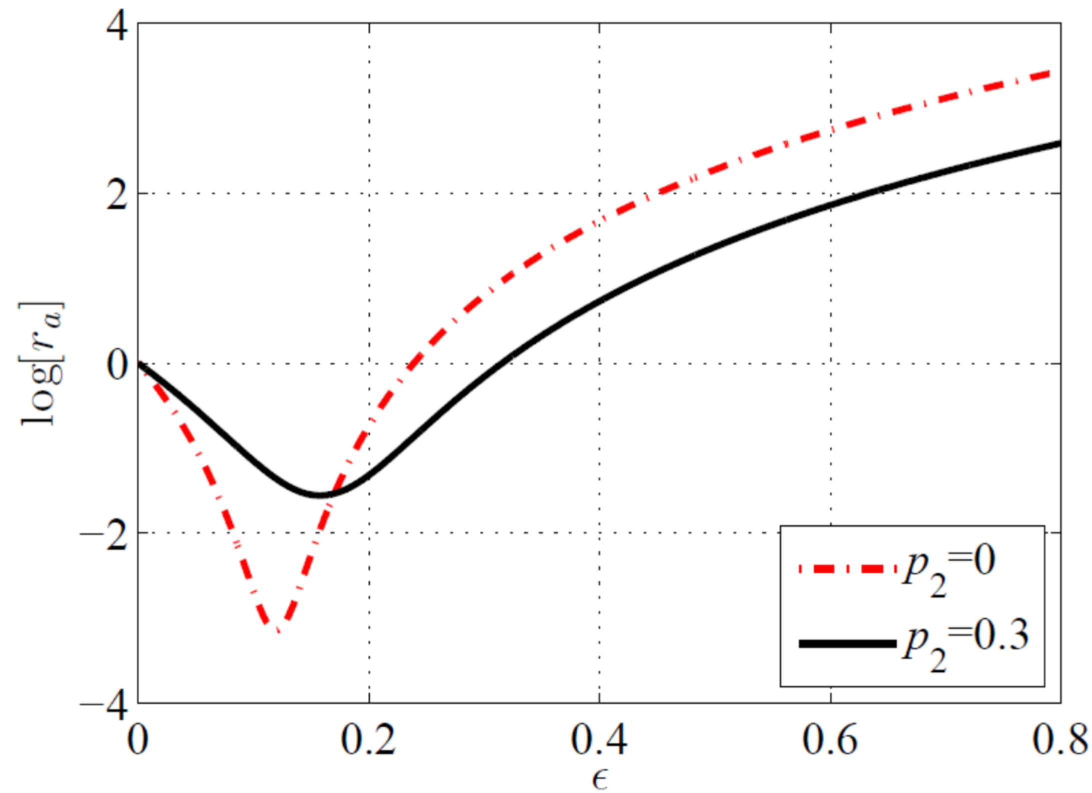
$$g_{D_1,\mathcal{E}_1}(d_1, \epsilon_1) = \begin{cases} 1/10 & \text{for } d_1 = 0, \epsilon_1 = 0.01 \\ 2/10 & \text{for } d_1 = 3, \epsilon_1 = 0.01 \\ 2/10 & \text{for } d_1 = 2, \epsilon_1 = 0.03 \\ 5/10 & \text{for } d_1 = 6, \epsilon_1 = 0.03 \end{cases}$$

$$g_{D_2,\mathcal{E}_2}(d_2, \epsilon_2) = \begin{cases} 1/10 & \text{for } d_2 = 0, \epsilon_2 = 0.01 \\ 1/10 & \text{for } d_2 = 1, \epsilon_2 = 0.01 \\ 2/10 & \text{for } d_2 = 3, \epsilon_2 = 0.03 \\ 6/10 & \text{for } d_2 = 2, \epsilon_2 = 0.03 \end{cases}$$



Example: Erdos-Renyi networks (1)

- Asymptotic convergence factor for $N = 10, p_1 = 0.8, p_2 = 0, 0.3$ and ϵ constant, varying
- Antagonistic interactions may enable consensus which is otherwise not possible
- Slower max possible convergence rate



$$r_a = (1 + \epsilon N(p_2 - p_1))^2 + 2\epsilon^2 (N-1)\big(p_1(1-p_1) + p_2(1-p_2)\big)$$

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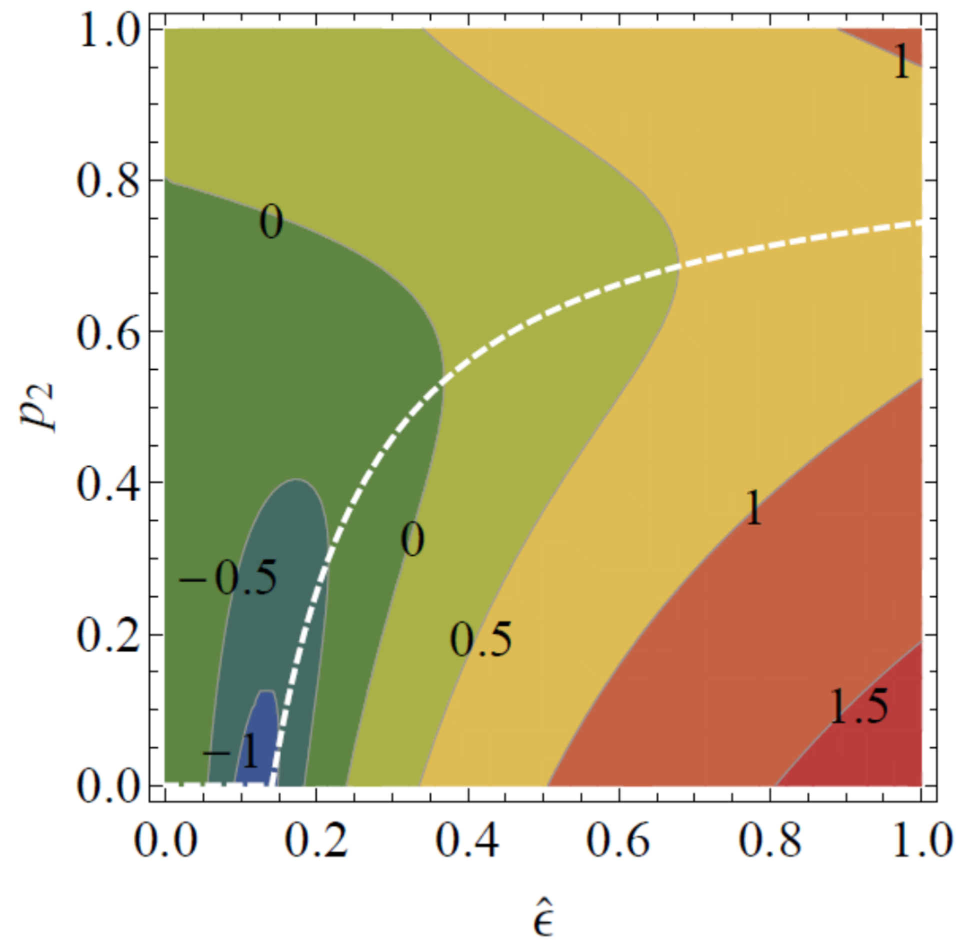
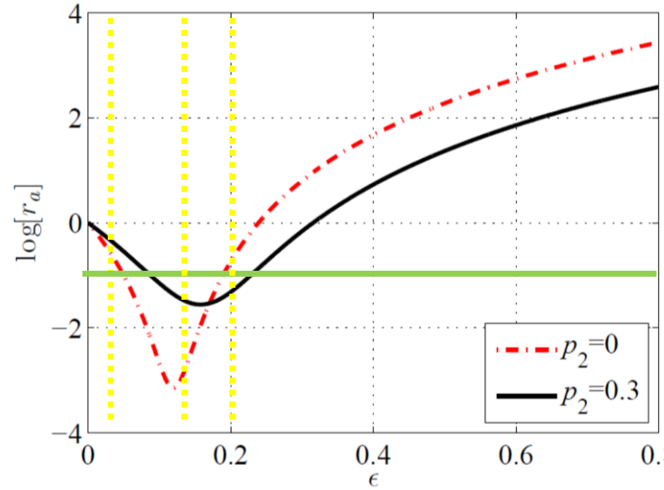
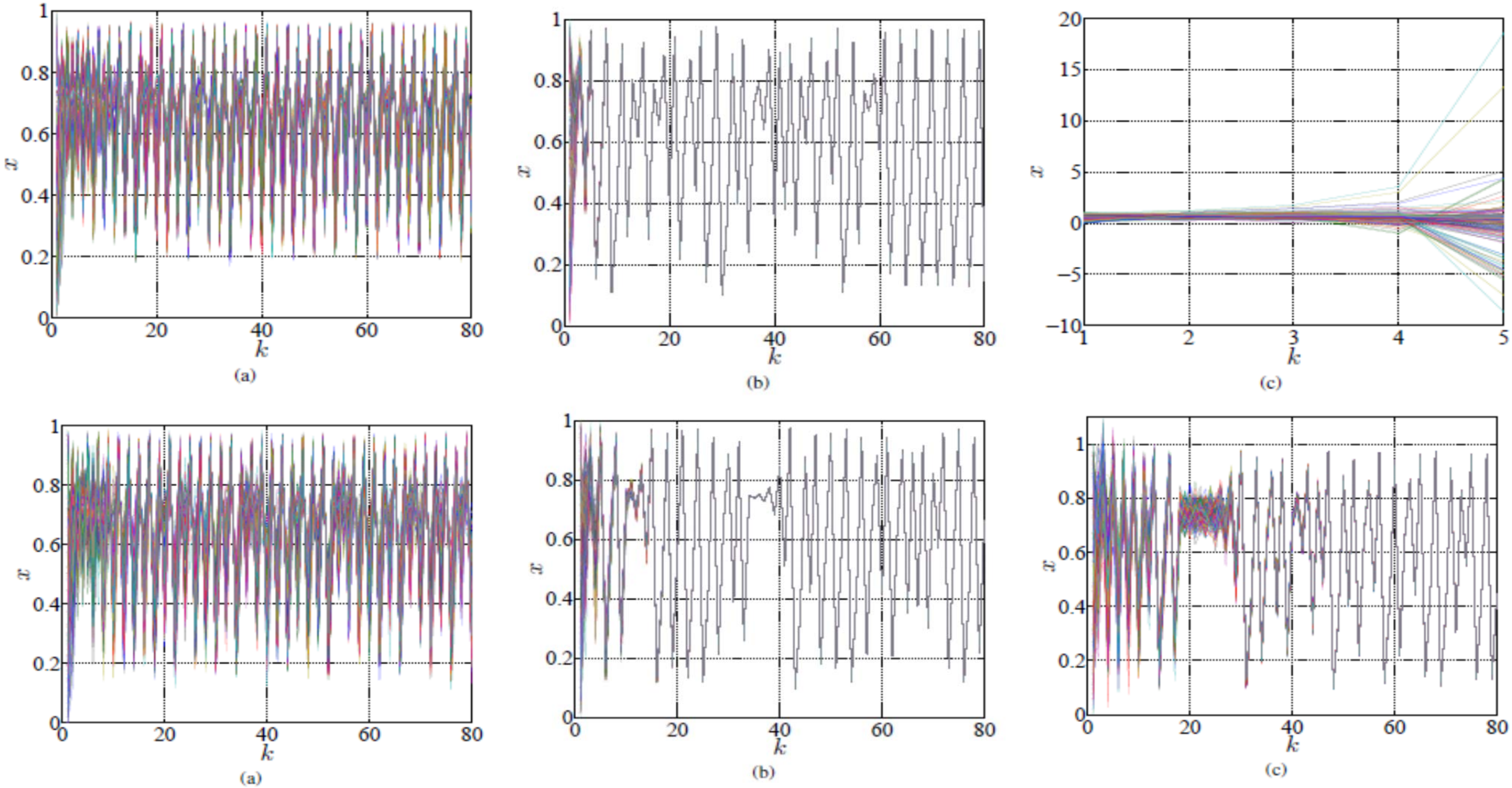


$$r_a = (1 + \epsilon N(p_2 - p_1))^2 + 2\epsilon^2 (N-1)\big(p_1(1-p_1) + p_2(1-p_2)\big)$$

Extend to synchronization

- $$x_i(k+1) = f(x_i(k)) - \sum_{j=1}^{N} [M]_{ij}(k) f(x_j(k))$$
- Sync condition: $r_a < -2h_{\max}$
- 200 logistic maps ($2h_{\max} = 0.97$)

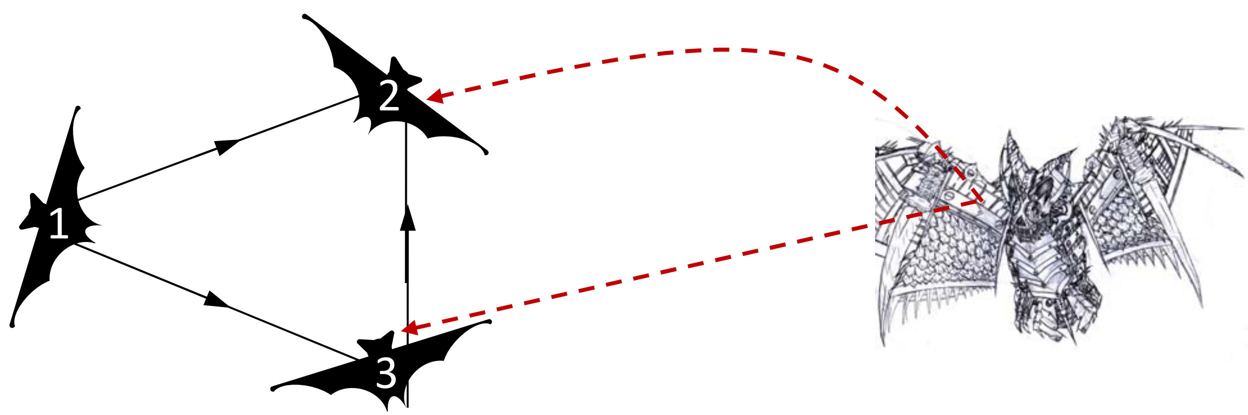




What does this mean for the model system?

- Collaborative/antagonistic interactions -> different communication and sensory modalities
- May give conflicting information that doesn't necessarily "cancel"

- Possible inspiration for animal-robot interactions



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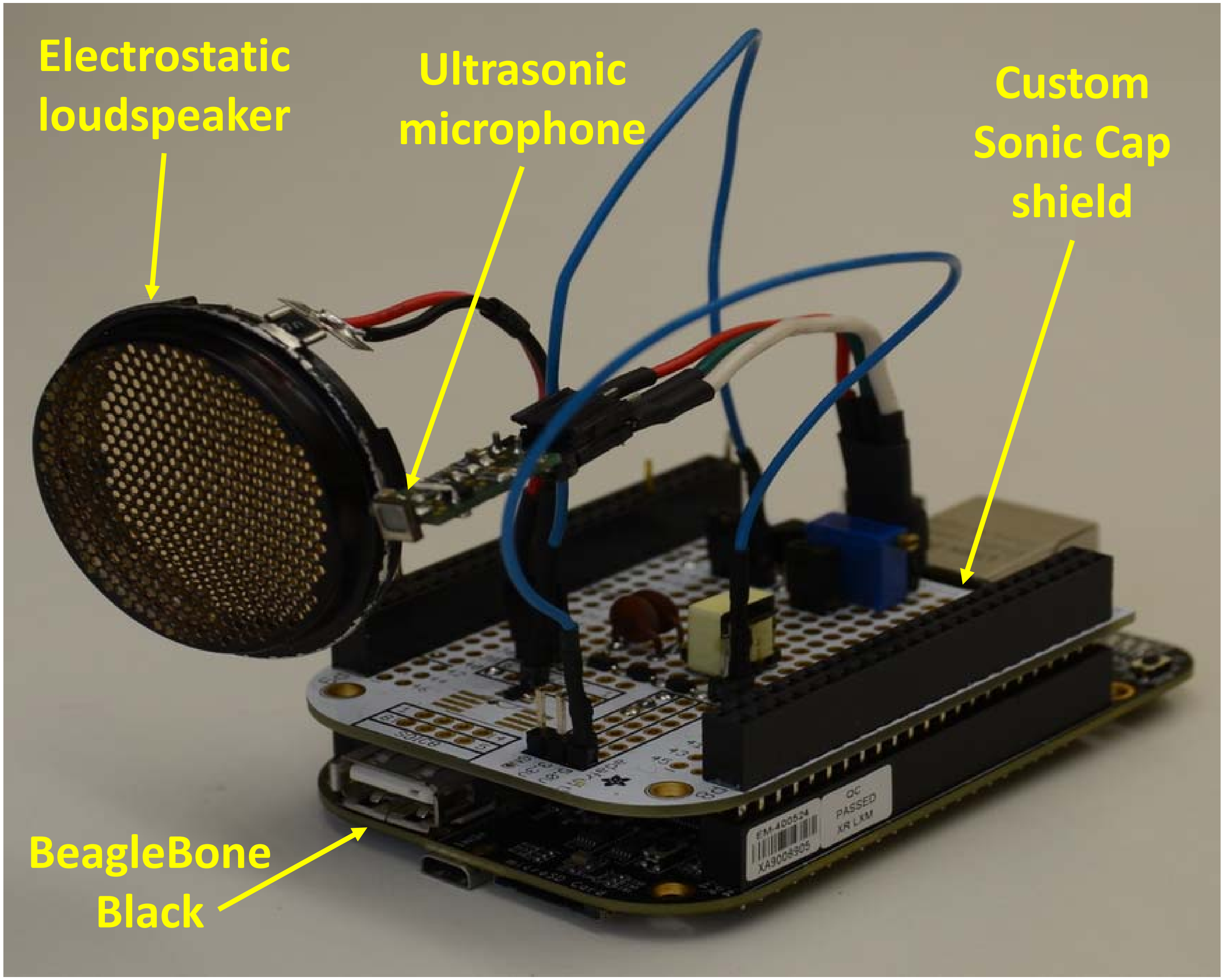
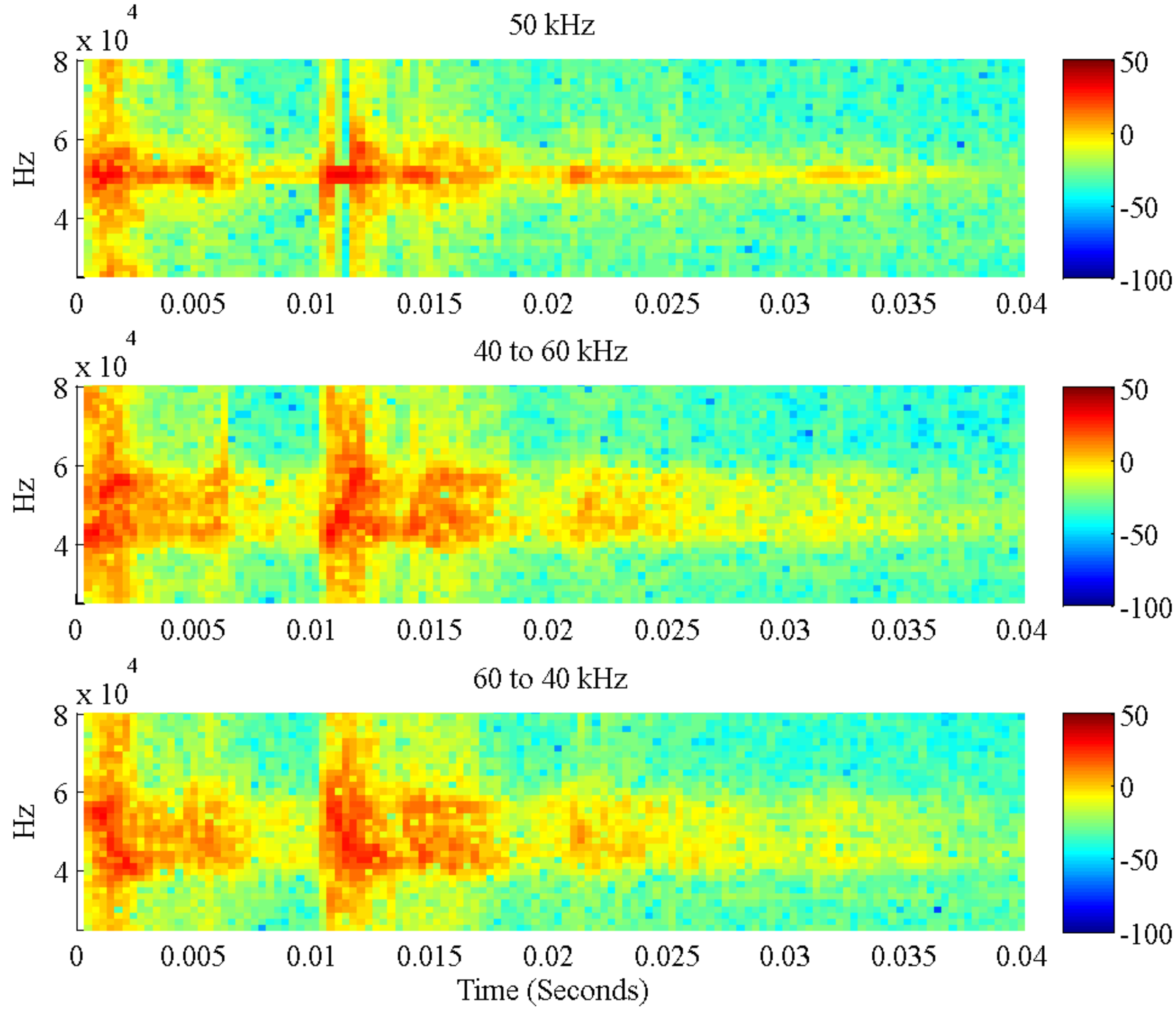
The Sonic Beagle



Experiments with target at 6 ft

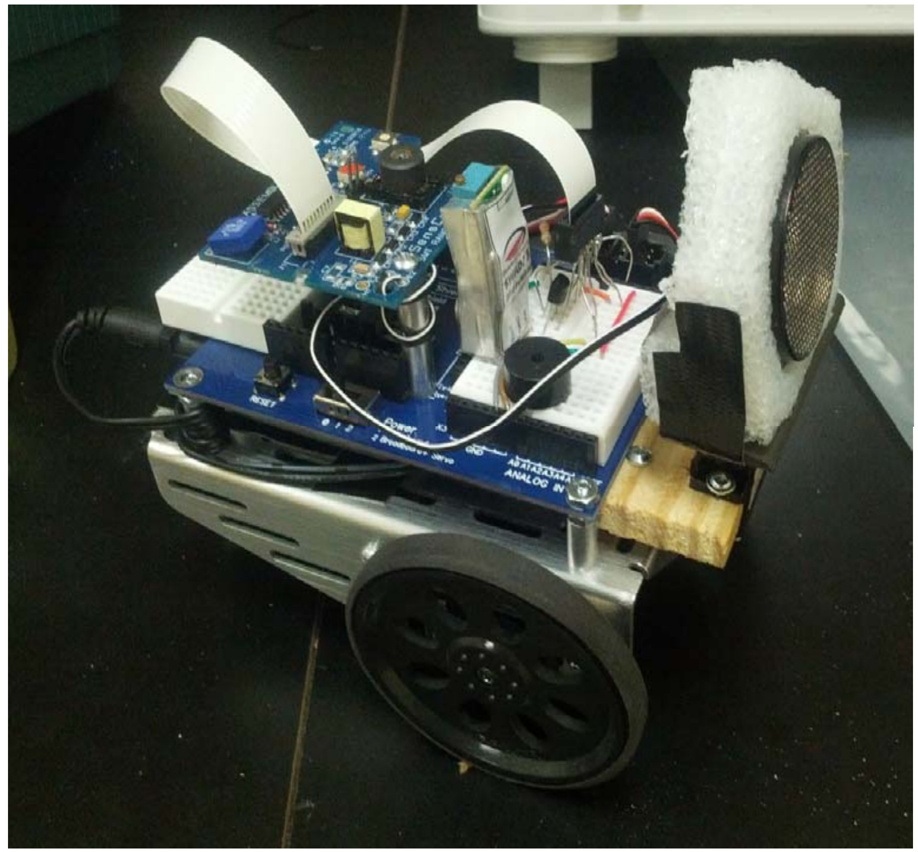


Time-of-flight information (0.011 s) is captured with additional frequency information can be encoded in

Where do we go from here?

- Sensorize mobile robots with frequency modulated sonar

- Design cooperative control algorithms for obstacle avoidance via collective sensing using transfer entropy results



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