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...


http://www.neuro.uni-bremen.de/~eurich/Teaching/Ws01/V5.html
Bats

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

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

(Chiroptera plate from Ernst Haeckel’s Kunstformen der Natur, 1904)
Bat echolocation strategies

• Frequency modulation

• Vocalization cessation

• Offensive jamming for hunting
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

\[
x_i: \text{bat } i's \text{ position vector} \\
v_i: \text{bat } i's \text{ velocity vector} \\
N: \text{number of bats} \\
r_s: \text{sensing range} \\
\phi: \text{angular sensing range}
\]
Modeling (1)

**Position update:**  
\[ x_i(t + \Delta t) = x_i(t) + v_i(t + \Delta t) \Delta t, \]
\[ i = 1, 2, \ldots, N \]

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

\( \alpha, \beta, \gamma \): 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 \( \tilde{E} \))  
\( \sigma \): unit vector in the positive \( y \) direction  
\( \omega \): random vector with Gaussian distribution for length, uniform for direction
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
Emit a pulse? (Bernoulli random variable)  

Yes → Use self echoes to obtain exact obstacle locations  

No → Eavesdrop peers’ echoes and pulses to obtain perturbed obstacle locations  

Perform velocity update to avoid obstacles whose exact or perturbed locations are in the repulsion zone  

Perform position update
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:

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

Number of collisions averaged over time and individuals

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

Weight to balance orders of magnitude
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
  \( r_s = 5\text{m}, \phi = 60^\circ \)
- 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.
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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
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:

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

with

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

From conspecific agents
Background on networks

Networks can be described equivalently as graphs and matrices

- Vertices $i=1,\ldots, N$
- 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)

$$D = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad A = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \quad L = \begin{bmatrix} 2 & -1 & -1 \\ 0 & 0 & 0 \\ 0 & -1 & 1 \end{bmatrix}$$
Conspecific model

- Homogeneous individuals from Abaid, Igel, and Porfiri 2012
- Draw traits from bivariate distribution: \( g_D, \varepsilon(d, \epsilon) \)
- Random variable \( D \) quantifies the cardinality of neighbor set
- Random variable \( \varepsilon \) quantifies each agents’ averaging weight or “stubbornness”
- \( d_1, d_2, \) and \( d_3 \) are realizations of \( D \)
- \( \epsilon_1, \epsilon_2, \) and \( \epsilon_3 \) are realizations of \( \varepsilon \)
- Weighted Laplacian matrix: \( M = \text{diag}([\epsilon_1, \epsilon_2, \epsilon_3])L \)
Modeling eavesdropping versus jamming: Collaborative and antagonistic interactions

- Collaborative pdf: $g_{D_1,\varepsilon_1}(d_1, \varepsilon_1)$
- Antagonistic pdf: $g_{D_2,\varepsilon_2}(d_2, \varepsilon_2)$
- $M(k) = M_1(k) - M_2(k)$

- 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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with

- $W(k)1_N = 1_N$ for all $k$ and typically use $W(k) = I_N - M(k)$
- $x(k) \in R^N$ is the state vector
- $k > 0$ is the time index
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
  \[ \xi(k + 1) = \overline{W}(k)\xi(k) \]

Stability of disagreement is taken as the consentability of total dynamics
Convergence to consensus (2)

Measuring the disagreement:

- Mean square stability: \( \lim_{k \to \infty} E[\|\xi_k\|^2] = 0 \) for all \( \xi_0 \)

- Asymptotic convergence factor: \( r_a = \sup_{\|\xi_0\| \neq 0} \lim_{k \to \infty} \left( \frac{E[\|\xi_k\|^2]}{\|\xi_0\|^2} \right)^{1/k} \)

- 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 \( R = I_N - \frac{1}{N} 1_N 1_N^T \)

Projection onto \( \text{span}(1_N \otimes 1_N)^\perp \)
### 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

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

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

\[
    \eta_1 = \phi_1 - \psi_1
\]

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Numerical validation

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

\[
g_{D_1,\varepsilon_1}(d_1, \varepsilon_1) = \begin{cases} 
1/10 & \text{for } d_1 = 0, \varepsilon_1 = 0.01 \\
2/10 & \text{for } d_1 = 3, \varepsilon_1 = 0.01 \\
2/10 & \text{for } d_1 = 2, \varepsilon_1 = 0.03 \\
5/10 & \text{for } d_1 = 6, \varepsilon_1 = 0.03 
\end{cases}
\]

\[
g_{D_2,\varepsilon_2}(d_2, \varepsilon_2) = \begin{cases} 
1/10 & \text{for } d_2 = 0, \varepsilon_2 = 0.01 \\
1/10 & \text{for } d_2 = 1, \varepsilon_2 = 0.01 \\
2/10 & \text{for } d_2 = 3, \varepsilon_2 = 0.03 \\
6/10 & \text{for } d_2 = 2, \varepsilon_2 = 0.03 
\end{cases}
\]
Example: Erdos-Renyi networks (1)

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

$$r_a = (1 + \epsilon N(p_2 - p_1))^2 + 2\epsilon^2 (N - 1)(p_1(1 - p_1) + p_2(1 - p_2))$$
Example: Erdos-Renyi networks (2)

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

\[
r_a = (1 + \epsilon N (p_2 - p_1))^2 + 2\epsilon^2 (N - 1) (p_1 (1 - p_1) + p_2 (1 - p_2))
\]
Extend to synchronization

- $x_i(k+1) = f(x_i(k)) - \sum_{j=1}^{N} [M]_{ij}(k)f(x_j(k))$

- Sync condition: $r_\alpha < -2h_{\text{max}}$
- 200 logistic maps ($2h_{\text{max}} = 0.97$)
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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Thank you! Questions?