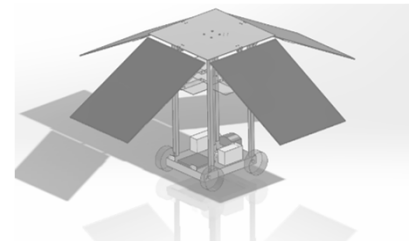
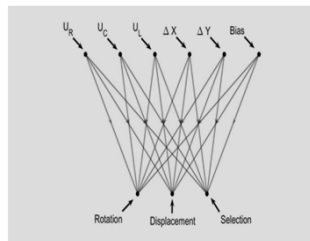
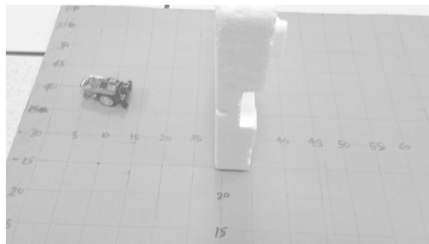


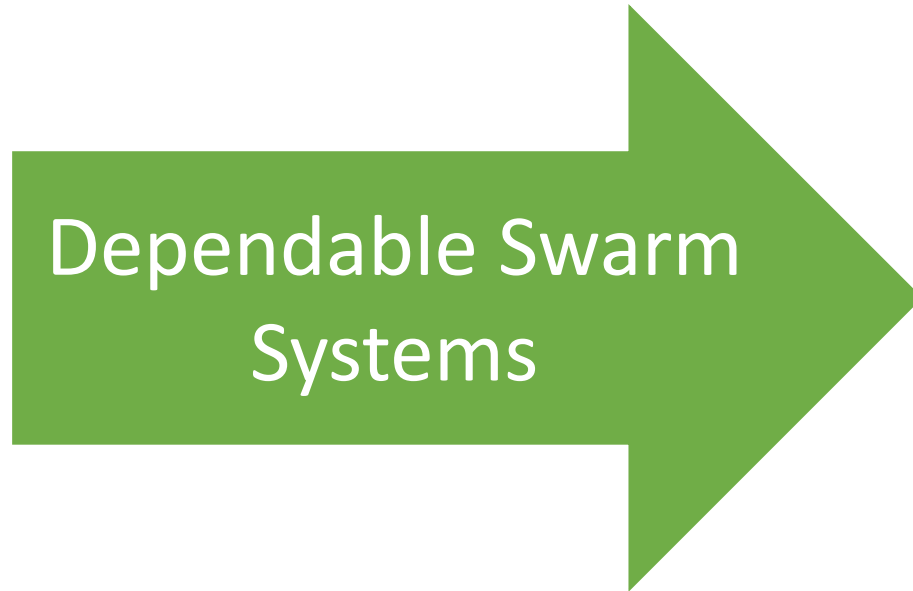
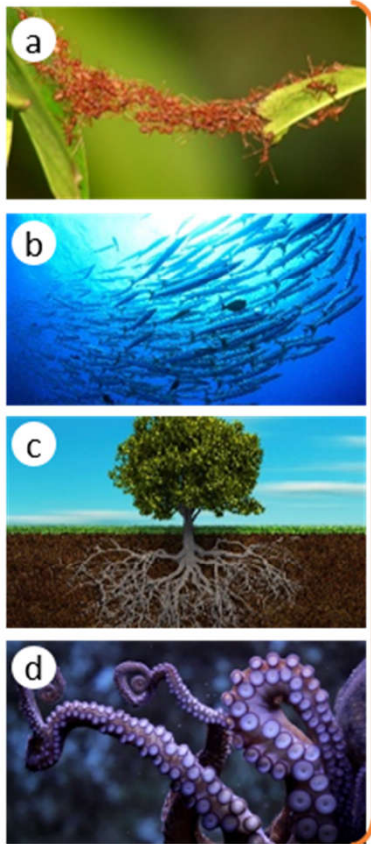
Oil Spill Monitoring and Disaster Response with Drone Swarms

Souma Chowdhury

Mechanical & Aerospace Engineering, University at Buffalo



Swarm Intelligence: the collective intelligence is greater than the sum of its parts

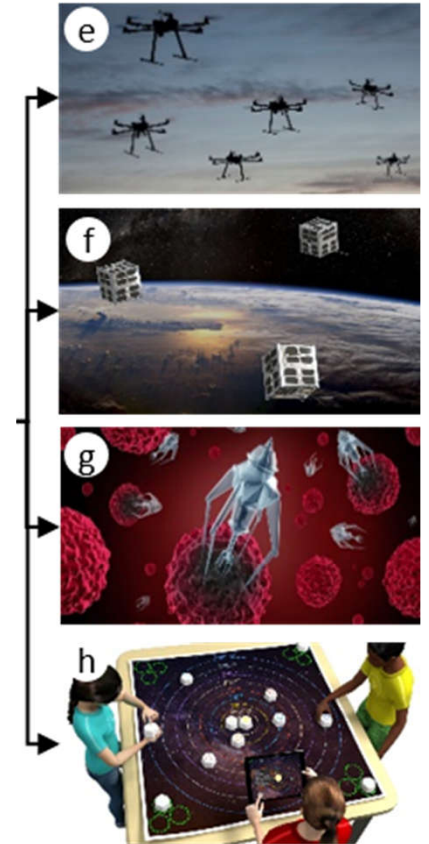


Efficient.....

Inexpensive.....

Fault Tolerant.....

Task Parallelism.....



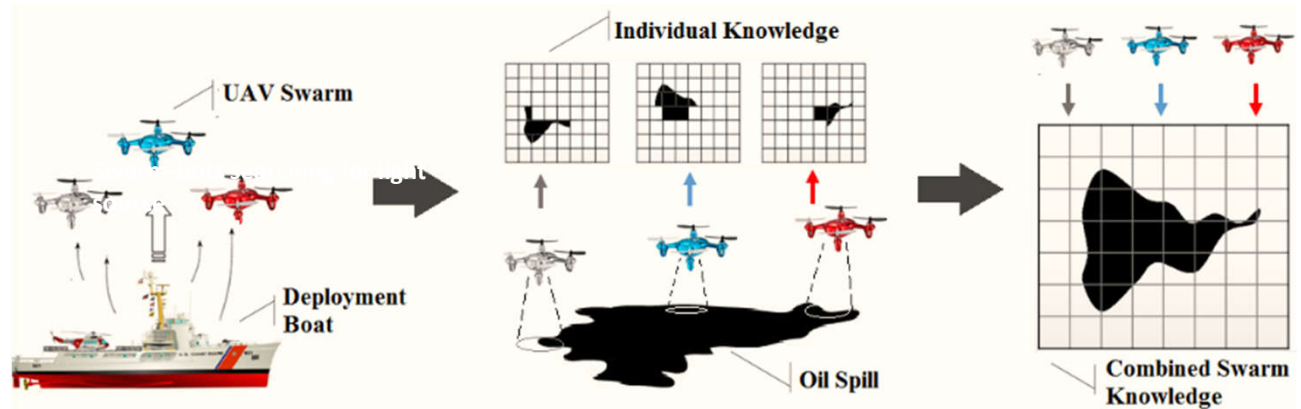
Outline

- Multi-drone Oil Spill Mapping (simulated)
- Multi-drone Flood Response (simulated)
- Scaled Indoor Experiments with Swarm-bots
- Other Drone Research

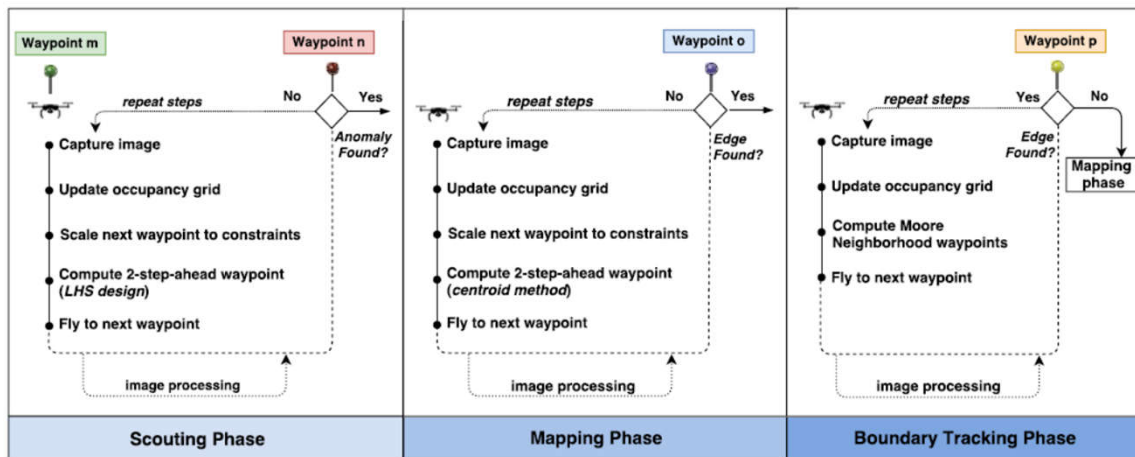
Multi-Drone Oil Spill Mapping

Swarm Systems: Simulated Oil Spill Mapping

GOAL:
 time-efficient,
 on-demand,
 inexpensive
 search/mapping



Mission Phases



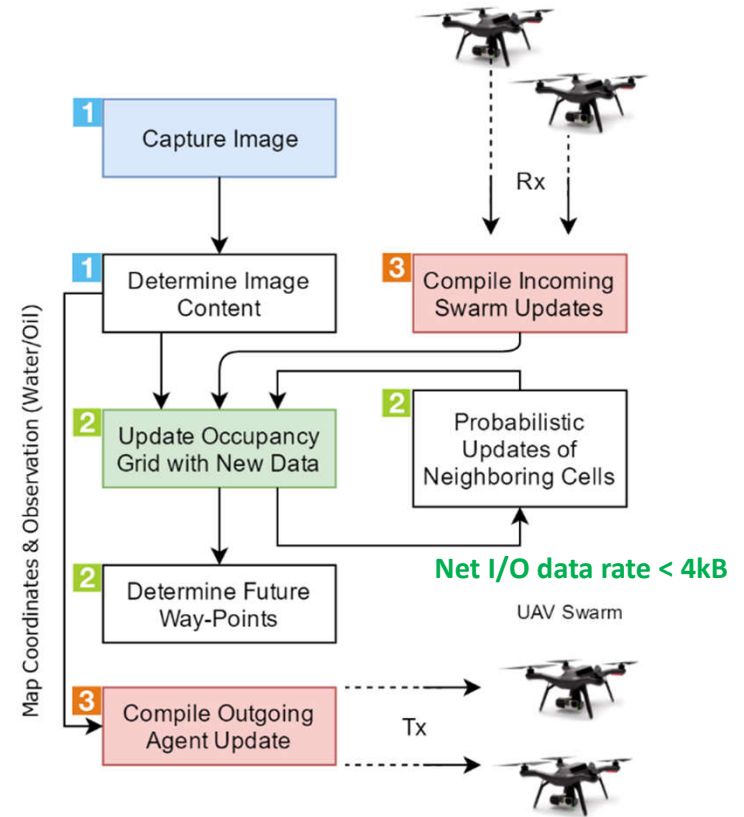
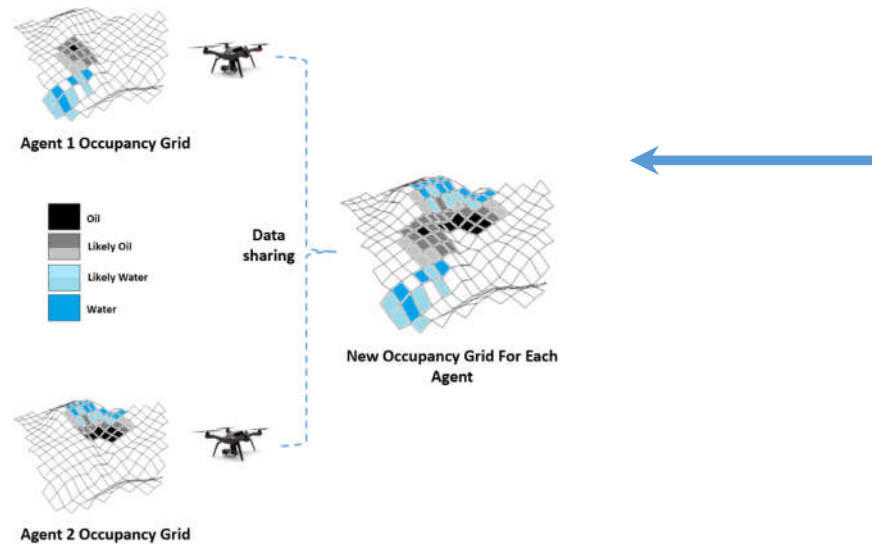
Drone Swarm Characteristics:

1. Fully decentralized and autonomous
2. Drones can talk to each other over a wireless network
3. Drones using sensing modality that provides real-time oil detection

Swarm Systems: PSOil

Particle Swarm Oil Spill Mapping (PSOil)

- Waypoint Planning: **Particle Swarm (PS) Mechanics**
- Knowledge Aggregation: **Stochastic Occupancy Grid**
- Knowledge Extraction: **Anomaly Detection**



$$v_i^{k+1} = \omega v_i^k + \beta_1 r_l (p_{l,i}^k - x_i^k) + \beta_g r_g (p_{g,i}^k - x_i^k) + \psi$$

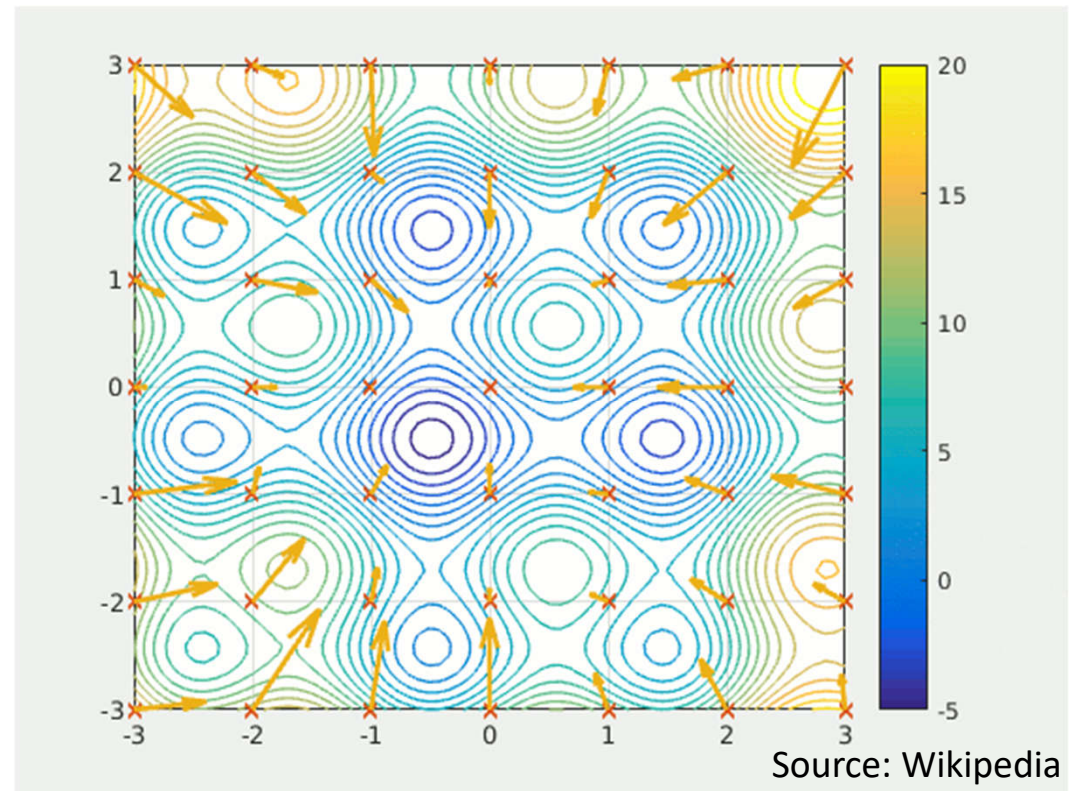
$$x_i^{k+1} = x_i^k + v_i^{k+1} \Delta t \quad \text{PS mechanics}$$

Swarm Systems: PSOil

The basic PS algorithm has to be largely modified, since

- Remaining areas of interest are continuously evolving (don't want to re-map already mapped oil).
- Drone have a cost in going from one location to another.

Particle Swarm (PS) Mechanics

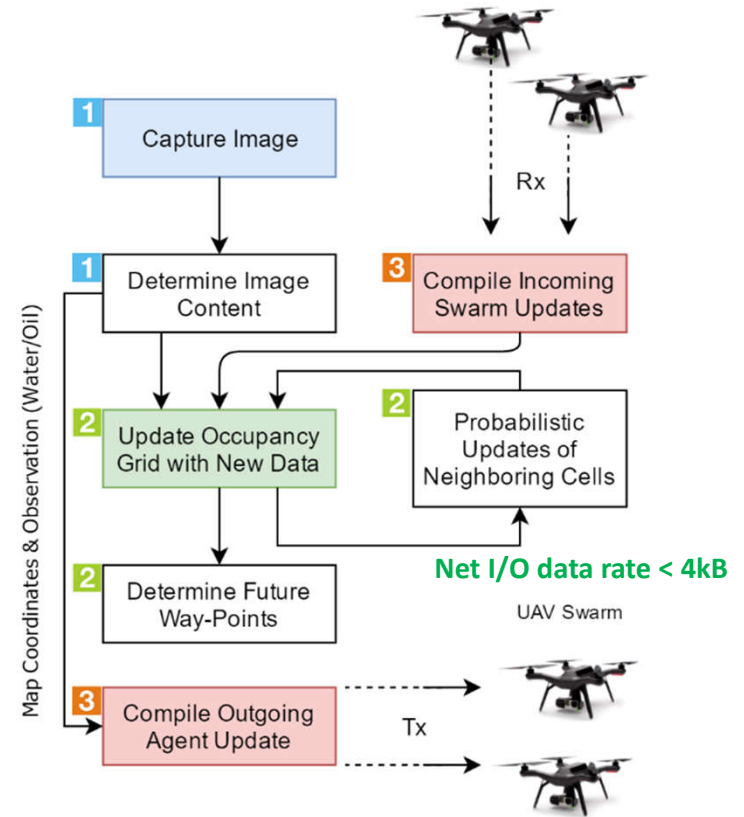
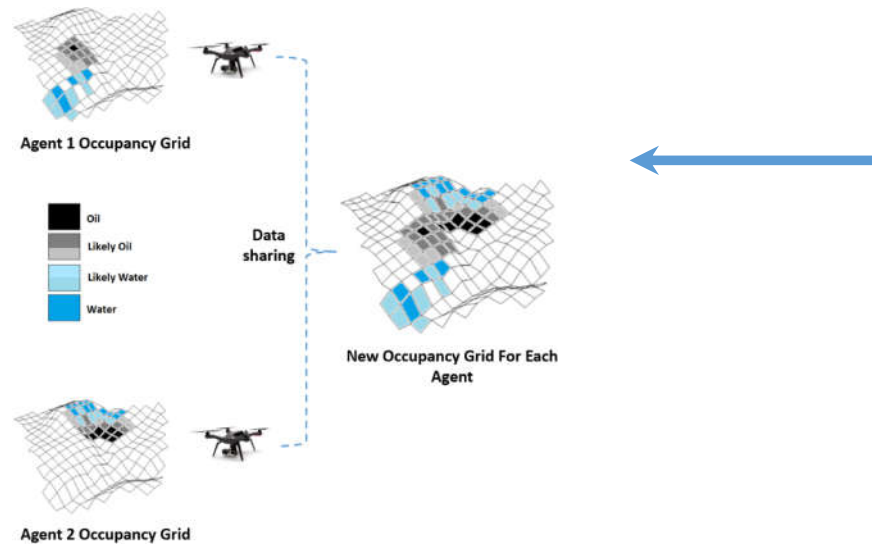


Area of interest: **decreases** from blue to yellow

Swarm Systems: PSOil

Particle Swarm Oil Spill Mapping (PSOil)

- Waypoint Planning: **Particle Swarm (PS) Mechanics**
- Knowledge Aggregation: **Stochastic Occupancy Grid**
- Knowledge Extraction: **Anomaly Detection**



$$v_i^{k+1} = \omega v_i^k + \beta_1 r_l (p_{l,i}^k - x_i^k) + \beta_g r_g (p_{g,i}^k - x_i^k) + \psi$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \Delta t \quad \text{PS mechanics}$$

Results Case Study MAP 1



Image 1 : Original Image

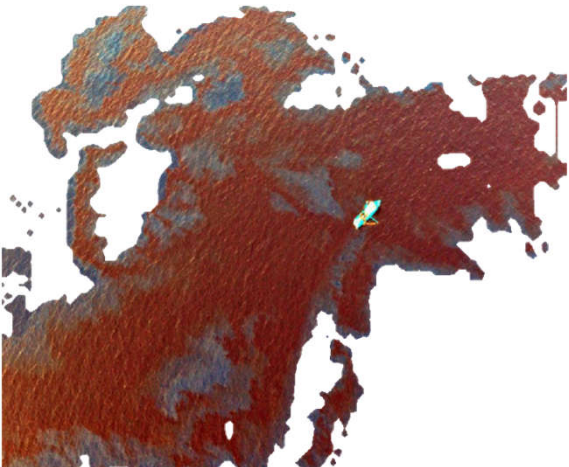
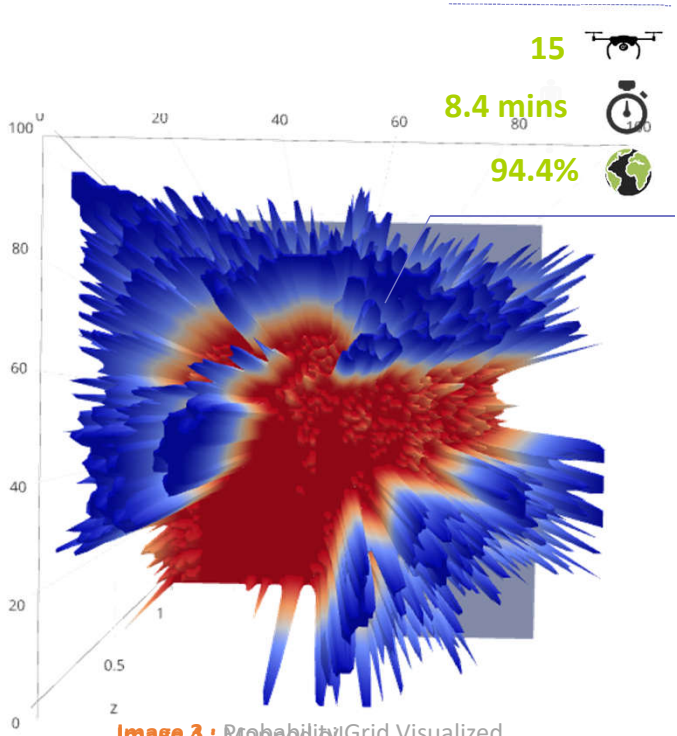


Image 2 : Mapped oil overlaid on original



Results Case Study MAP 2



Image 1 : Original Image



Image 2 : Mapped oil overlaid on original

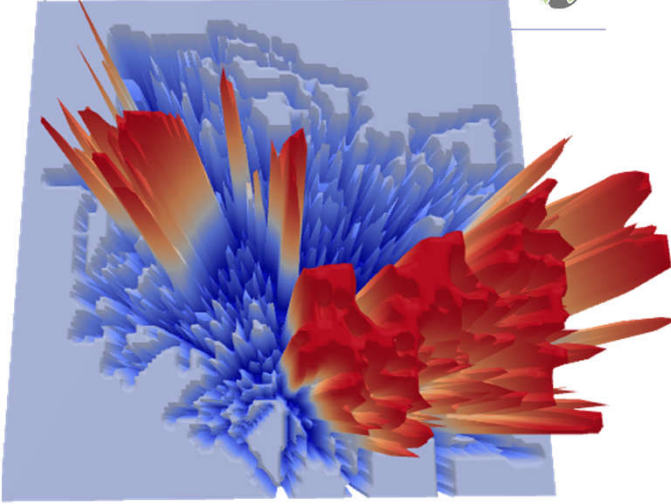





Image 4 : Mapped Grid Visualized

21 
12.7 mins 
93 % 

Results Case Study MAP 3

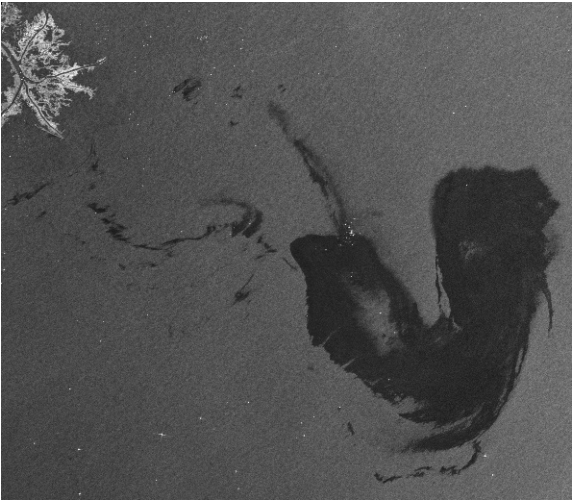


Image 1 : Original Image



Image 2 : Mapped oil overlaid on original

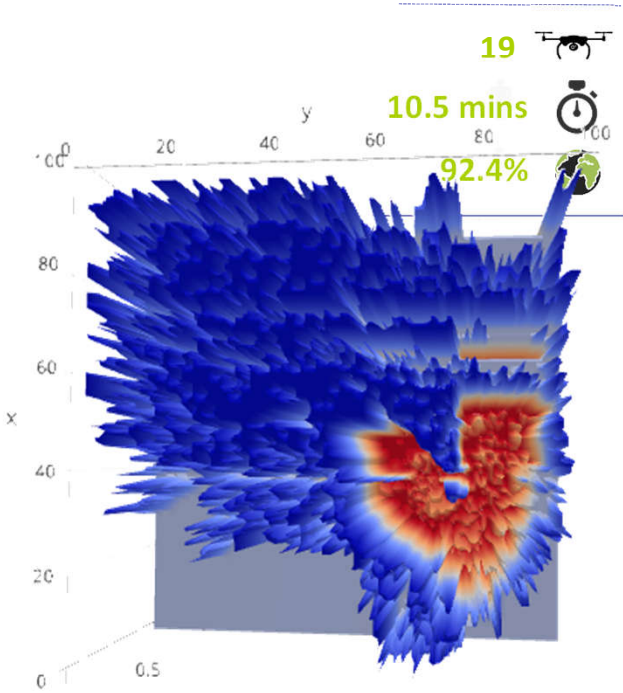


Image 3 : Probability Grid Visualized

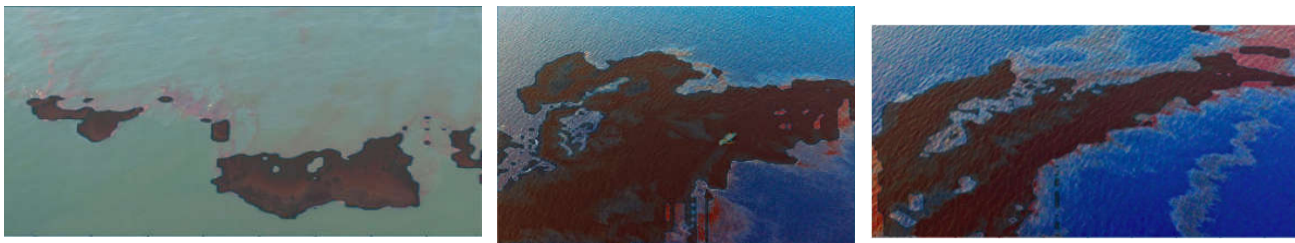
PSOil: Performance Evaluation

	Percent Identified [%]	Total Time [sec]
PSOil - Image 1	88.1 ± 6.3	843.0 ± 222.4
mTSP - Image 1	(prescribed coverage)	150
Spiral Search - Image 1	95.6	1582
Random Walk ^a - Image 1	72.9 ± 14.9	1031.0 ± 296.5
Exhaustive Search	100.0	2081.0

^a Remaining Random Walk results can be found in the Appendix.

PSOil is significantly better than random walk and spiral algorithm in terms of both % identified and total time

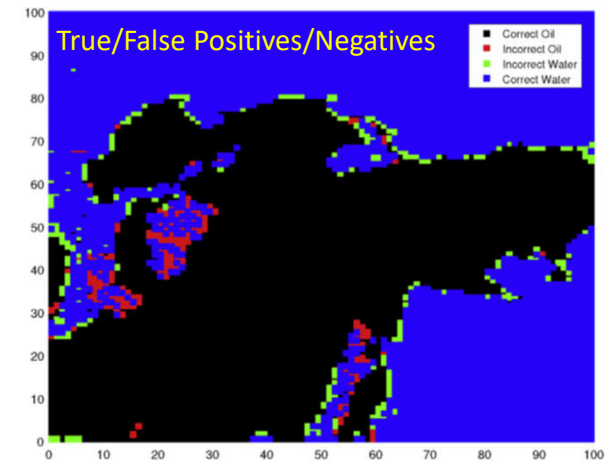
Image 1



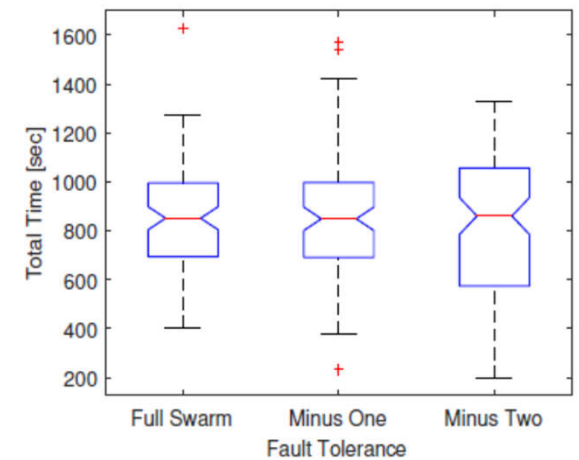
Lighter shade represents undiscovered oil

5-drone teams

1 image/5 sec capture rate



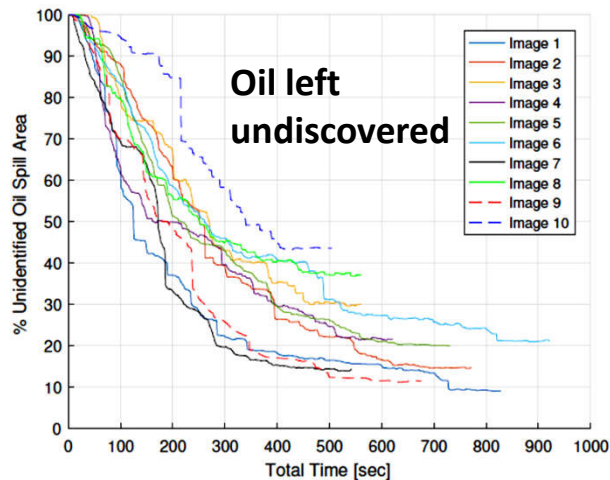
Fault tolerance to sudden loss of agents



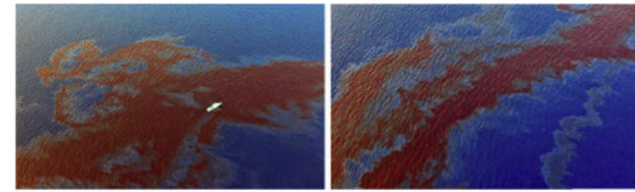
Results Summary

Method - Case	% Oil Identified	Total Time [s]	Distance Traveled [km]
PSOil - Image 1	88.1 ± 6.3	843.0 ± 222.4	58.9 ± 15.8
PSOil - Image 2	80.8 ± 5.0	720.4 ± 156.4	51.5 ± 11.3
PSOil - Image 3	60.4 ± 24.4	725.5 ± 251.4	51.0 ± 17.7
PSOil - Image 4	70.8 ± 20.0	767.5 ± 250.0	54.2 ± 17.6
PSOil - Image 5	82.7 ± 9.7	919.0 ± 224.0	64.8 ± 15.8
PSOil - Image 6	71.2 ± 7.9	775.7 ± 187.0	52.1 ± 12.6
PSOil - Image 7	81.1 ± 11.8	884.3 ± 220.6	60.3 ± 15.1
PSOil - Image 8	69.7 ± 10.0	597.9 ± 147.0	42.9 ± 10.5
PSOil - Image 9	84.0 ± 6.8	825.2 ± 204.4	52.7 ± 12.9
PSOil - Image 10	55.3 ± 10.2	673.2 ± 240.0	38.2 ± 13.6

Note that the results are reported in the [mean ± std-dev] format.



Challenging ones due to complexity and poor contrast

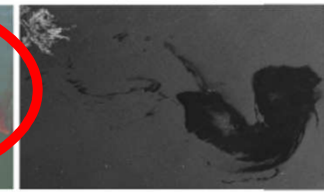


(a) Test Image 1

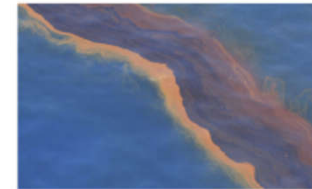
(b) Test Image 2



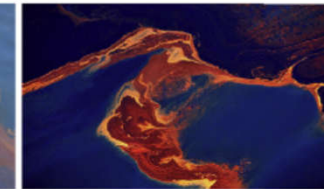
(c) Test Image 3



(d) Test Image 4



(e) Test Image 5



(f) Test Image 6



(g) Test Image 7



(h) Test Image 8



(i) Test Image 9



(j) Test Image 10

Time Sensitive Task Allocation in Swarm Systems

Multi-Drone Flood Victim Response

GOAL:

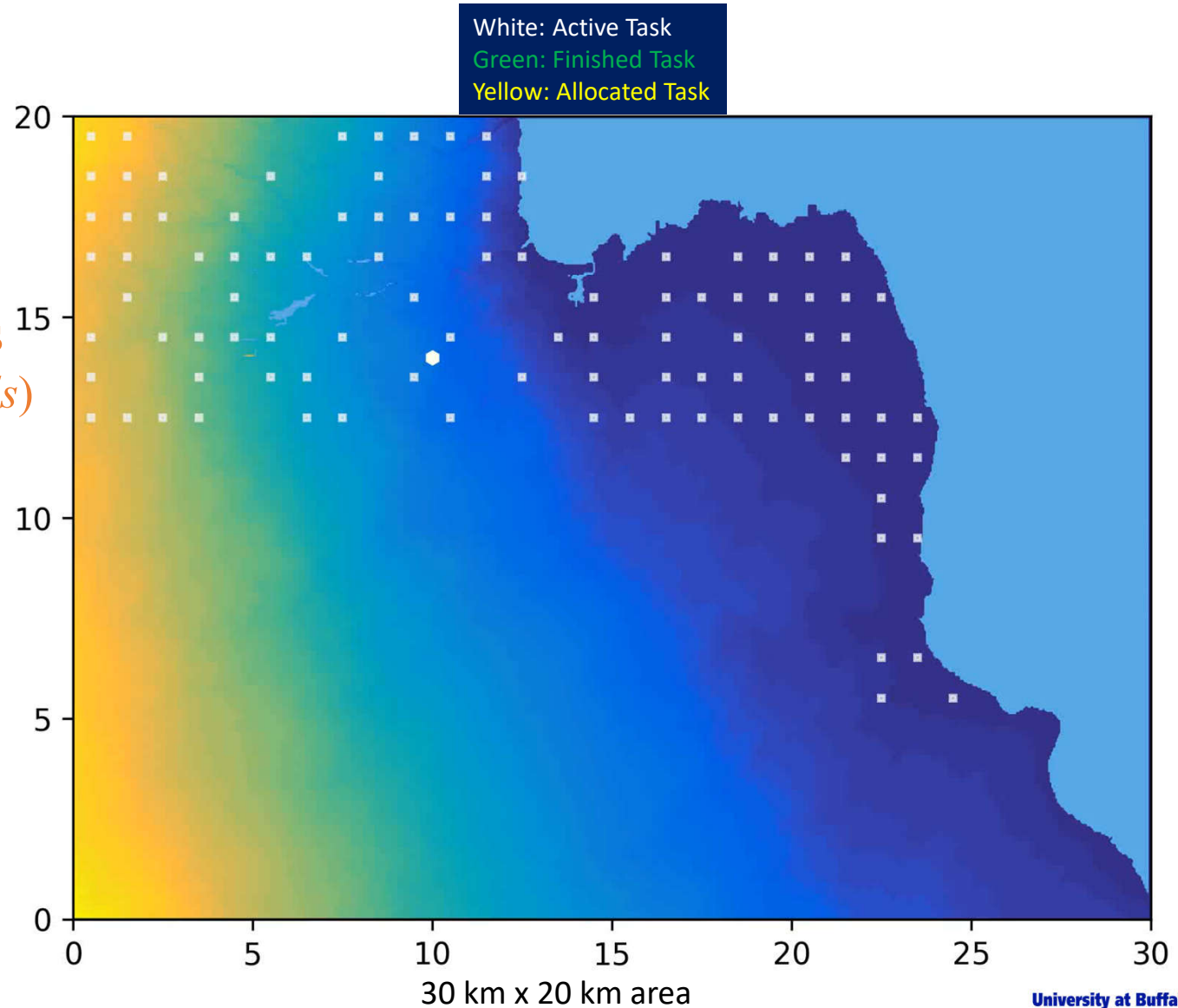
Deliver survival kits

To victims at different
known locations,

Within specified deadlines
(attributed to rising flood levels)

Drone Swarm Characteristics:

- Fully decentralized planning.
- Each UAV can carry 5 packages at a time, and has limited range.
- Simulations used, based on a very recent flood event, Tropical Storm Lane on August 28th 2018, at the west side of the Big Island of Hawaii, South Hilo district.



Algorithms for Task Allocation

Centralized

$$\max_{x_{ijs}^r, y_{is}^r} \sum_{s \in \mathcal{H}} \frac{1}{s} \sum_{r \in \mathcal{R}} \sum_{i \in \hat{\mathcal{T}}} y_{is}^r$$

subject to

$$\sum_{j \in \mathcal{T}} x_{ijs}^r = y_{is}^r; \quad i \in \mathcal{T}, s \in \mathcal{H}, r \in \mathcal{R}$$

$$\sum_{i \in \mathcal{T}} x_{iks}^r - \sum_{j \in \mathcal{T}} x_{kjs}^r = 0; \quad k \in \hat{\mathcal{T}}, s \in \mathcal{H}, r \in \mathcal{R}$$

$$\sum_{j \in \mathcal{T}} x_{0js}^r \geq y_{is}^r; \quad s \in \mathcal{H}, r \in \mathcal{R}$$

$$\sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{H}} y_{is}^r \leq 1; \quad i \in \hat{\mathcal{T}}$$

$$\sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{H}} x_{ijs}^r \leq 1; \quad i \in \mathcal{T}, j \in \mathcal{T}$$

$$\sum_{i \in \hat{\mathcal{T}}} y_{is}^r \leq Q; \quad s \in \mathcal{H}, r \in \mathcal{R}$$

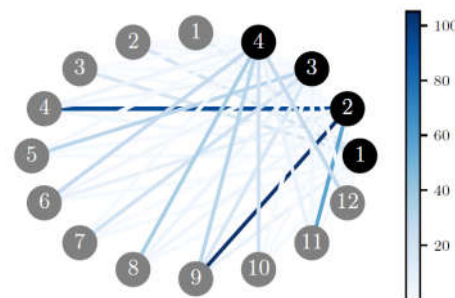
$$\sum_{i, j \in \mathcal{T}^e} d_{ij} x_{ijs}^r \leq \Delta_{\text{range}}; \quad s \in \mathcal{H}, r \in \mathcal{R}$$

Solving an integer linear programming problem

Decentralized (Dec-MRTA)



1 Weighted Bigraph Construction



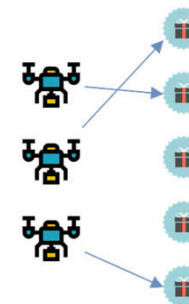
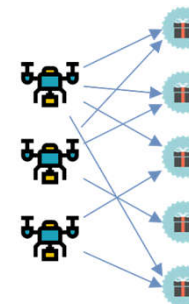
2 Robots' Incentive Computation

$$w_{ri} = \begin{cases} \max(0, \Delta_r - \epsilon) \cdot \exp\left(-\frac{t_i^r}{\alpha}\right) & \text{if } t_i^r \leq \delta_i \\ 0 & \text{Otherwise} \end{cases}$$

where $\Delta_r = l^r - (d_{ri} + d_{i0})$

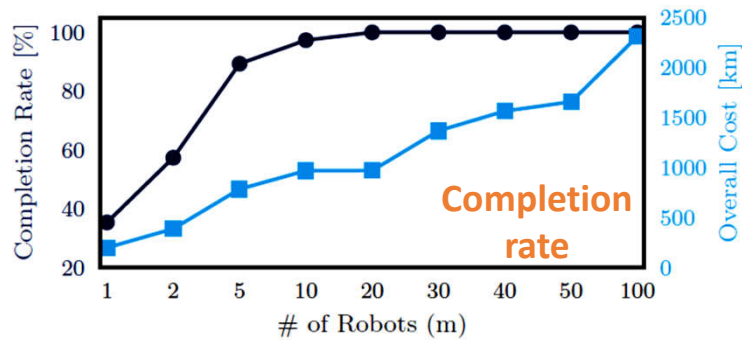
3 Maximum Weight Matching

Solving matching problem for the weighted bipartite graph.

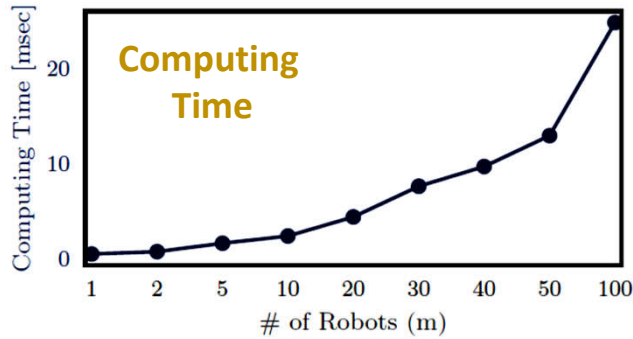


Flood Response Results

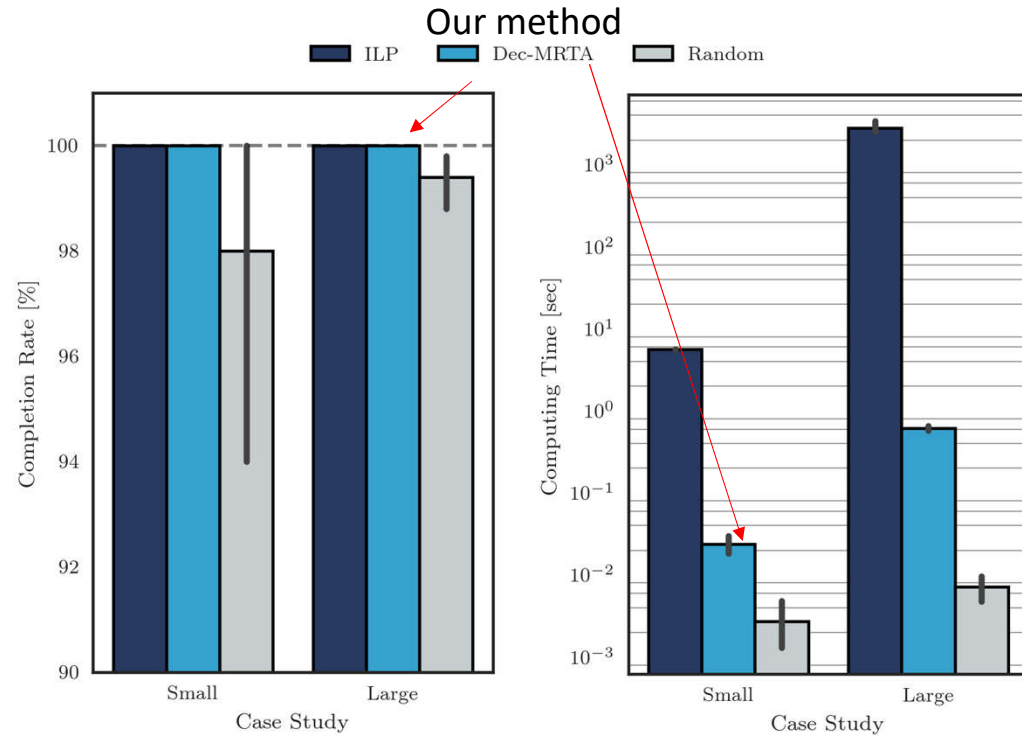
1,000 victim locations to visit



(a) Mission Performance



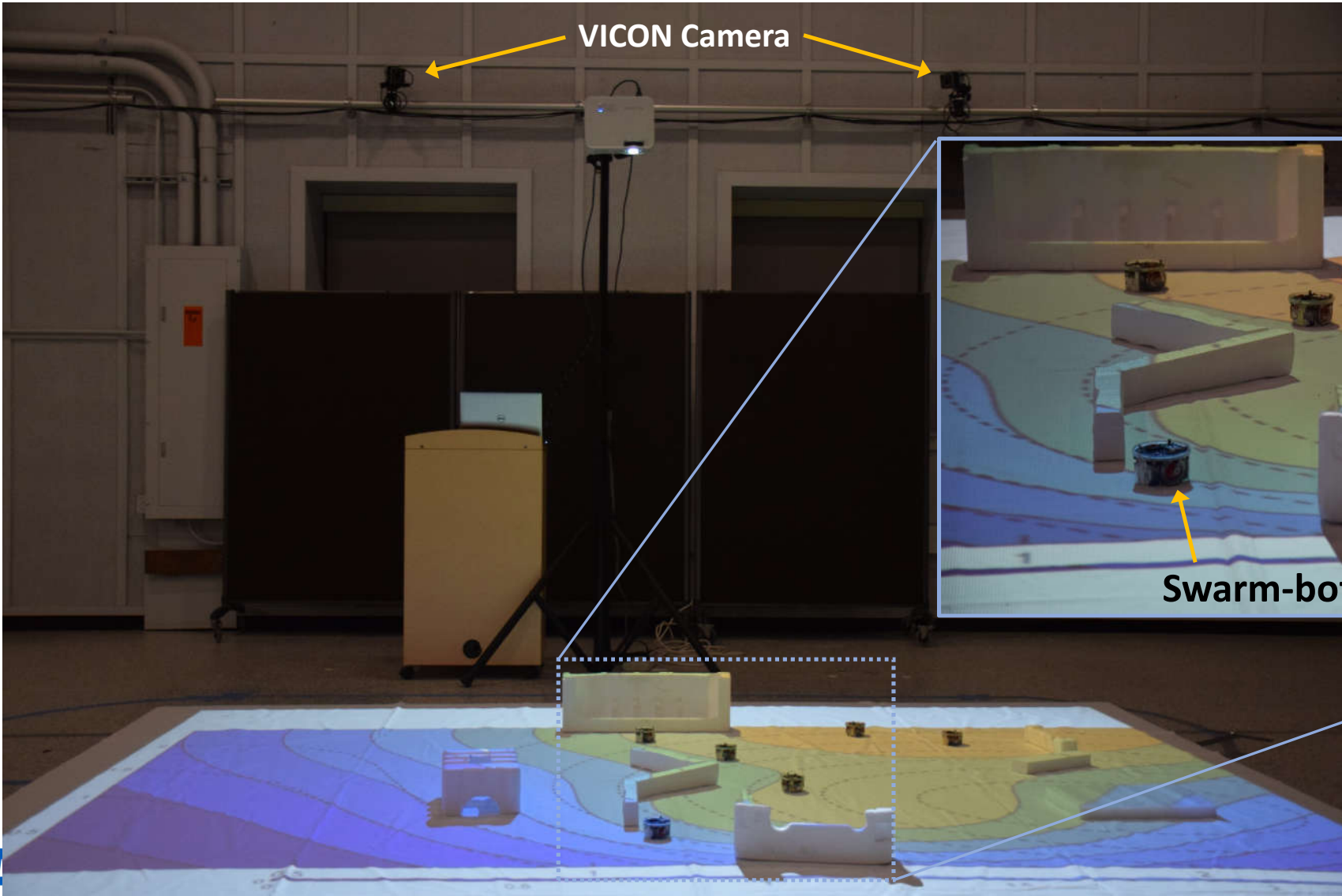
(b) Computational Efficiency



- ✓ Performance of our method (Dec-MRTA) is close to that of the centralized ILP, and much better than random.
- ✓ Our method is ~1000 times faster in computing time.
- ✓ Important to know swarm size sweet spots.

Swarm-bot Testbed

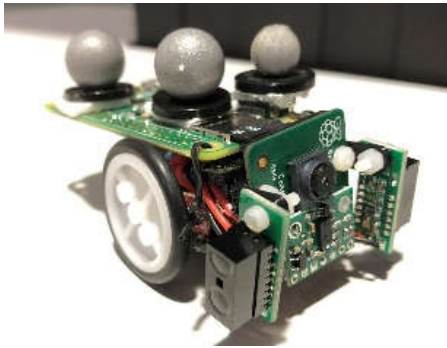
Scaled-down physical experiments



VICON Camera

Swarm-bot

Swarm-bot Ground & Aerial Platforms:



Swarm-bot developed in-house



E-Puck: off-the-shelf swarm-bot

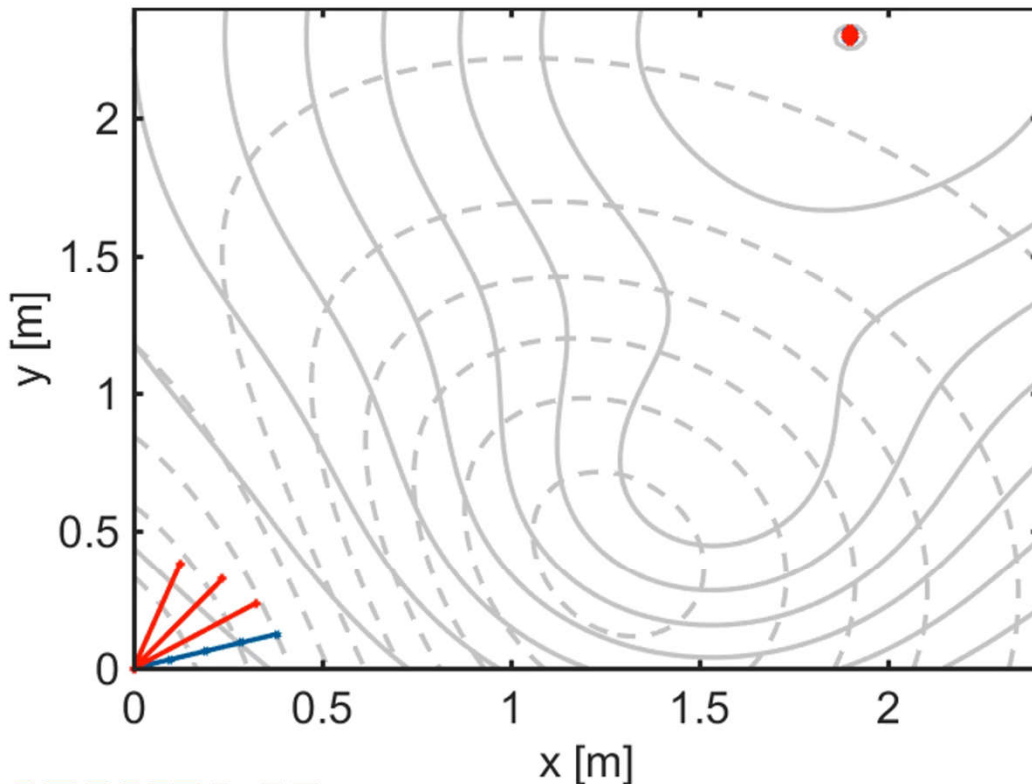


Crazyfly: off-the-shelf swarm-drone

Simulated Environment to be projected

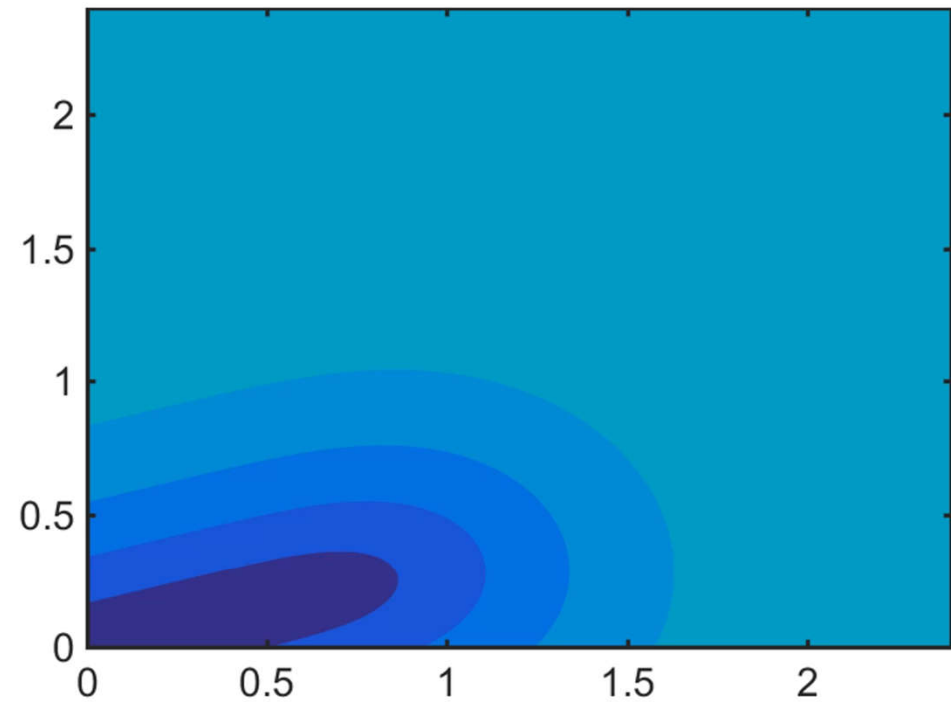
Evolving knowledge response

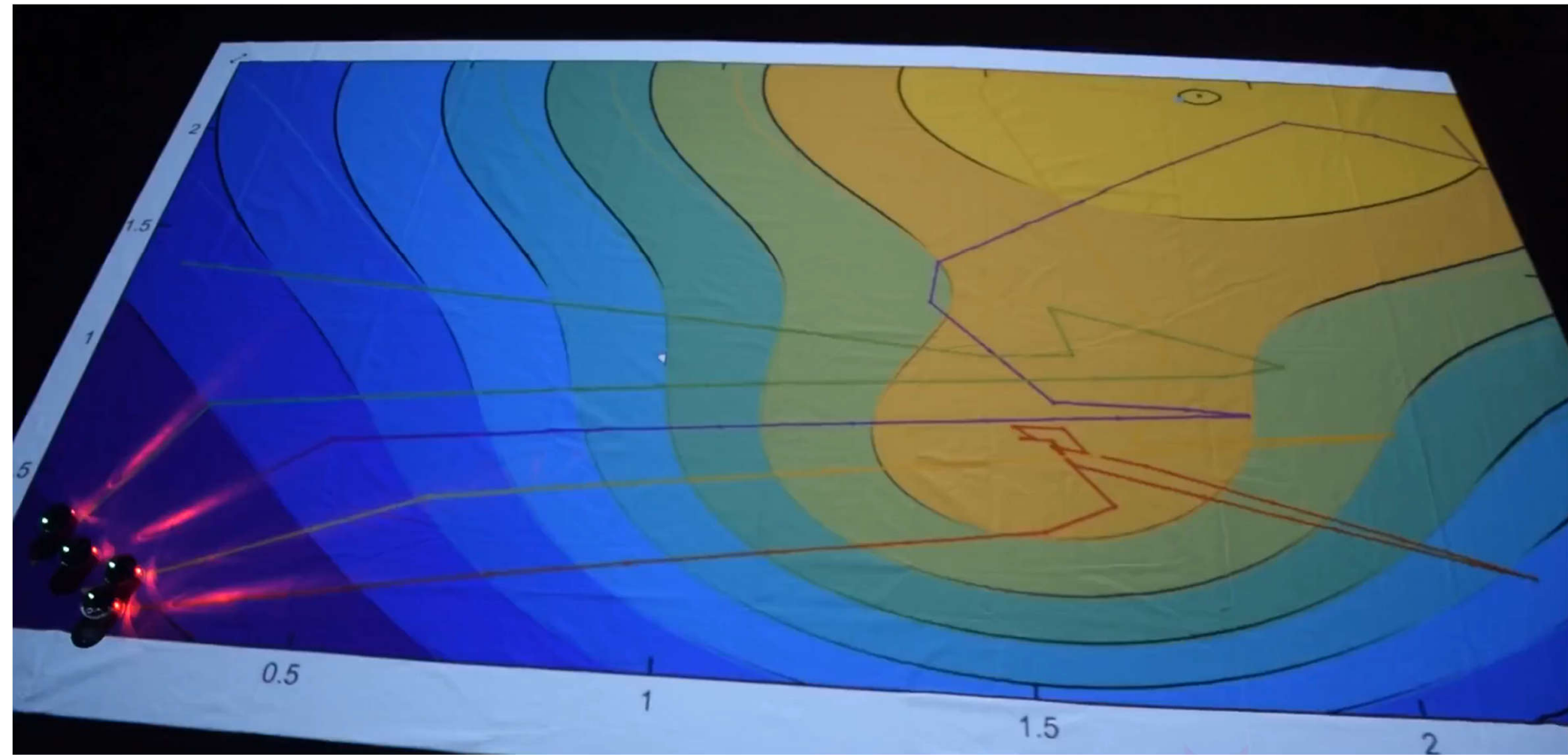
Solid: actual signal distribution Dashed: current belief of swarm



Lack of Knowledge

blue – low lack. Yellow: high lack





Swarm Systems: Concluding Remarks

Accomplishments

- **Nature-inspired** and **graph-based swarm systems** have been developed for time-sensitive mapping (oil spill mapping), and search and respond (e.g., flood response) applications.
 - Mapping performance far exceeding that of known swarm-based solutions
 - Computing costs in response mission are 1000 times smaller than centralized approaches
- Scaled down physical implementations (over projected environment) is being developed and tested right now, in a high-bay motion capture facility.

Next Steps:

- Hardware-in-the-loop testing.
- Natural environment testing, subject to communication constraints.

Swarm Systems: Concluding Remarks

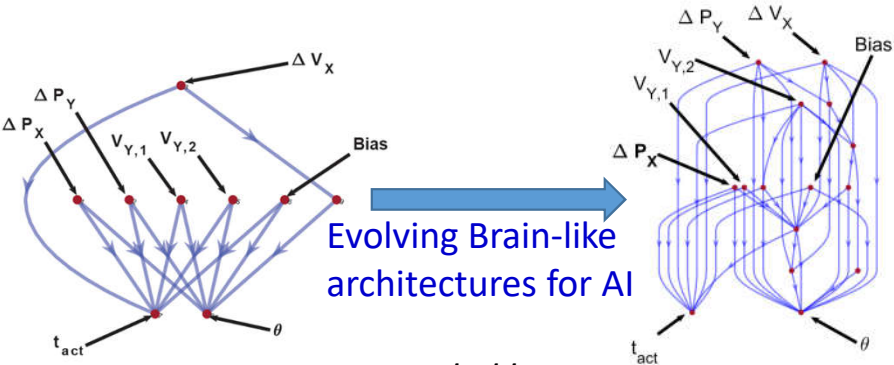
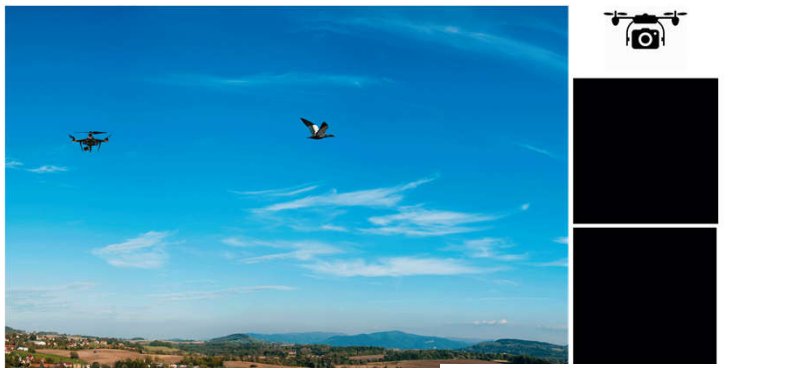
Key Challenges

- Lack of access to infrastructure and partners for natural environment testing.
- FAA policy restricting field experimentation with large autonomous drone swarms.
- High-fidelity online sensor data interpretation.

Other Research in Autonomous Drones

Other UAV (Drone) research in our lab

UAV Collision Detection & Avoidance

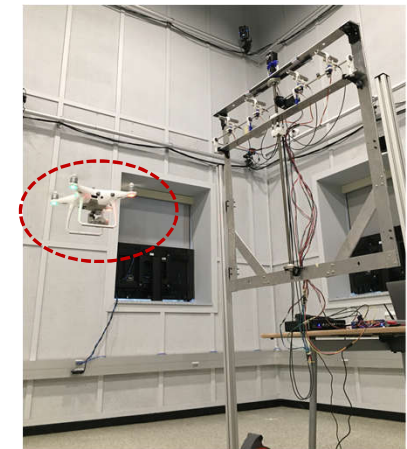
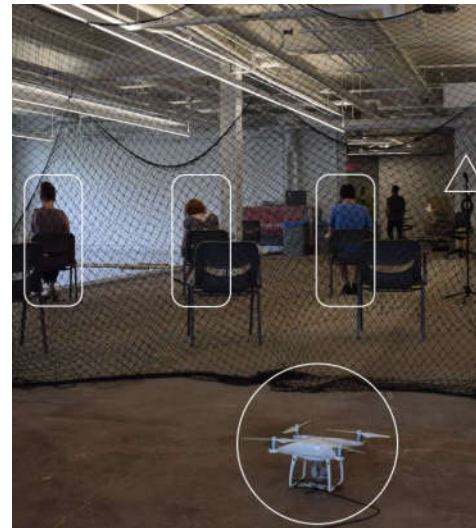


Evolving Brain-like architectures for AI

Funded by DARPA Physics of AI program

ADAMS LAB
ADAPTIVE DESIGN ALGORITHMS, MODELS & SYSTEMS

Impact of Drone Noise on Operators

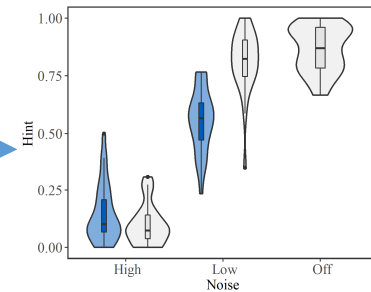


Acoustic characterization

Human subject study

Impact on hearing

Funded by U Buffalo SMART seed Grant



ADAMS Lab Facilities



MakeBlock

RaceCar

Falcon

Skeleton

Phoenix

Kakapo

SwarmBot II

SwarmBot III



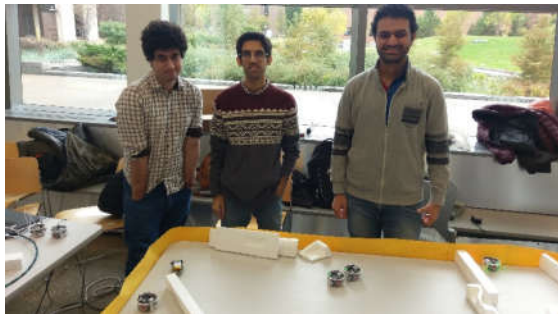
Turtlebot

DJI Matrice

E-Pucks

Outreach Activities

UB Robotics Day 2018



ADAMS LAB
ADAPTIVE DESIGN ALGORITHMS, MODELS & SYSTEMS

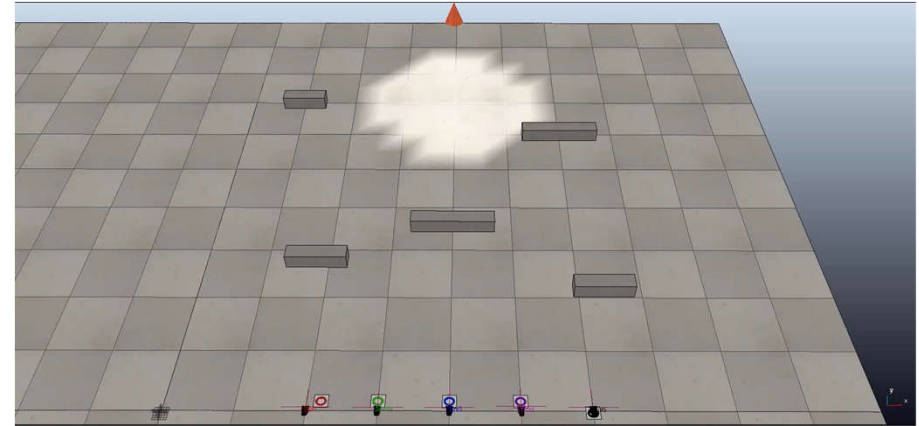
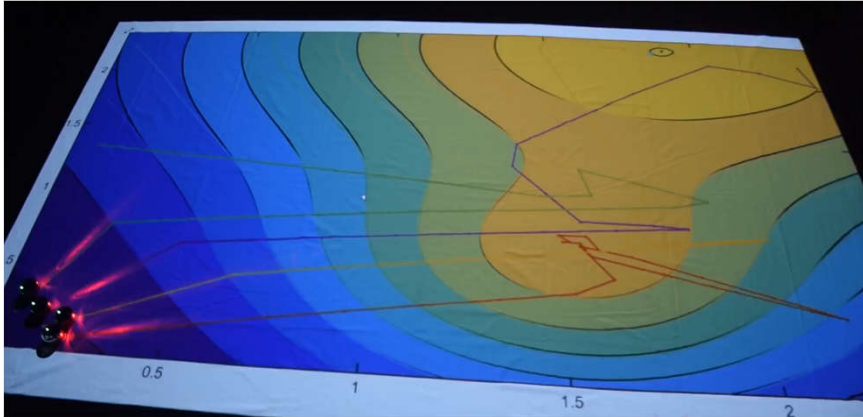
UB Emergency Drill 2017



With Buffalo Fire Dept.
& Buffalo Police Dept.

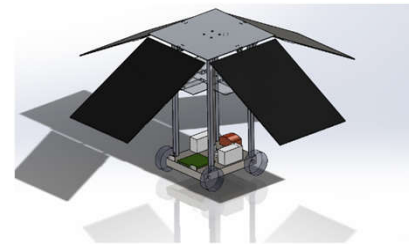
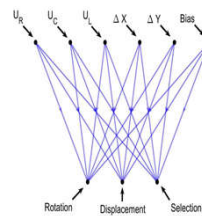
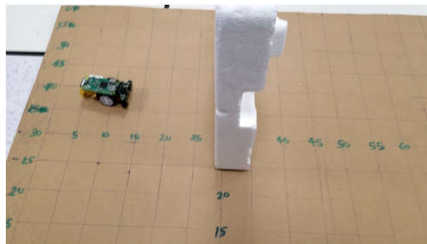


University at Buffalo
The State University of New York



Thank You

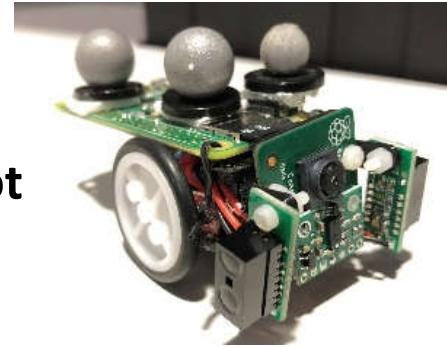
QUESTIONS?



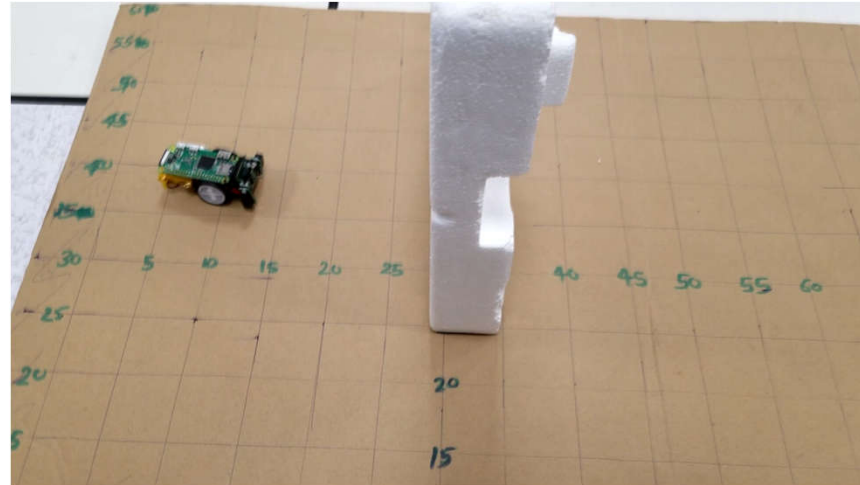
Innovative platforms developed in-house



Energy Autonomous UGV



Swarmbot

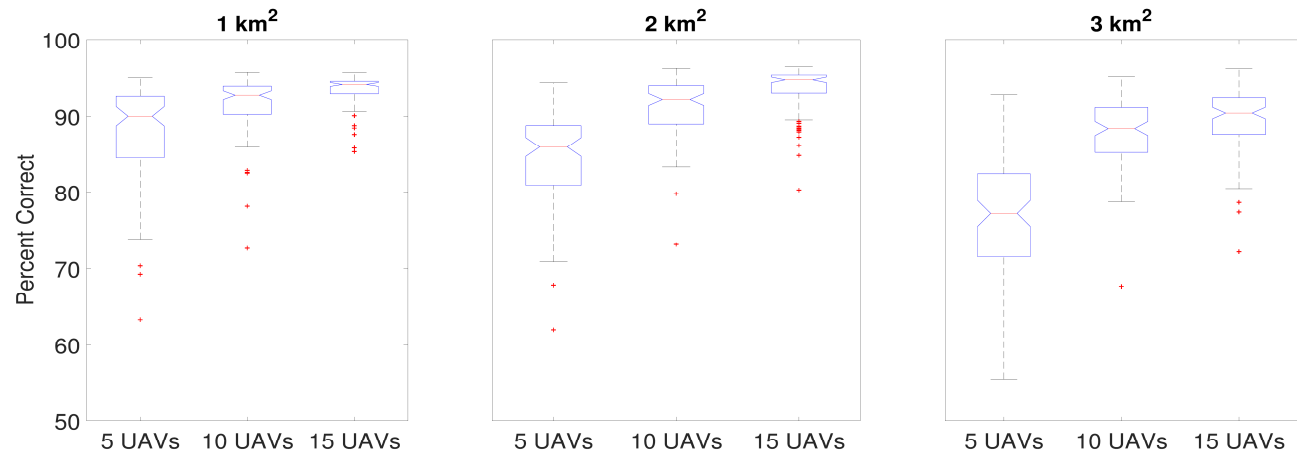


Extra Slides

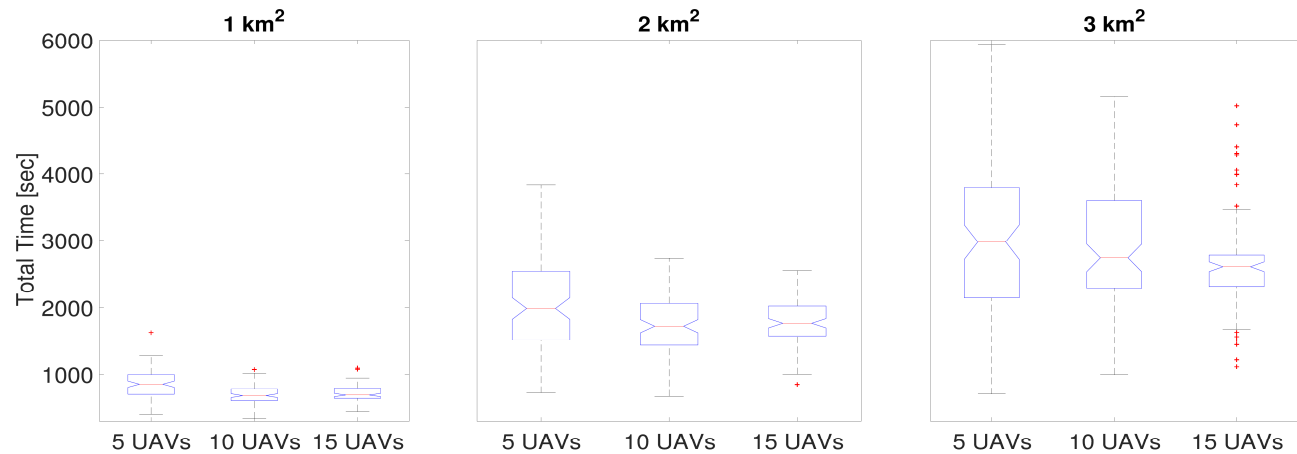


DRONE: SPARK
AVG: 78 DB
MAX: 81 DB
PEAK: 77 DB
EQUIVALENT: ALARM CLOCK

Scalability of the swarm: PSOil



(a) *Percent oil correctly identified*



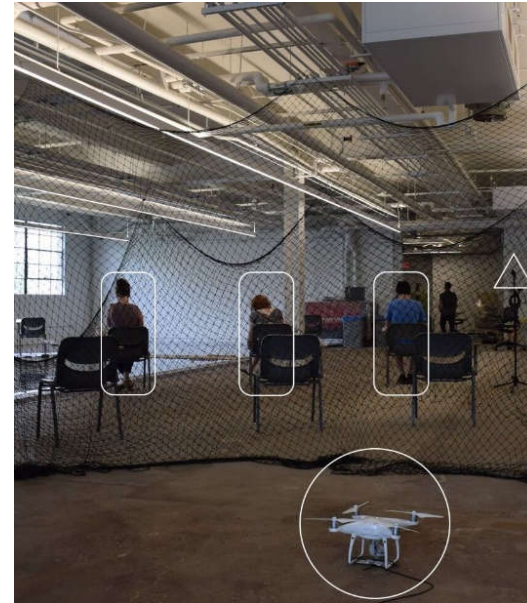
(b) *Total search time*

UAV Noise Impact Modeling & Mitigation

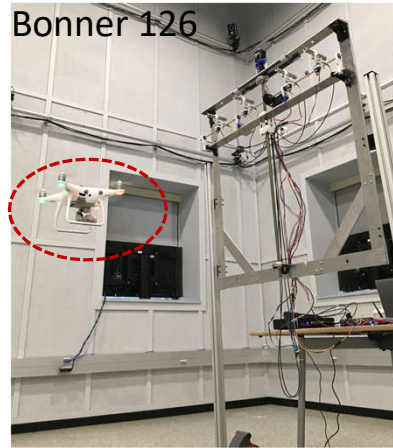
Sponsored by
SMART Center of Excellence @UB

Primary Developments

Human Subject Experiments



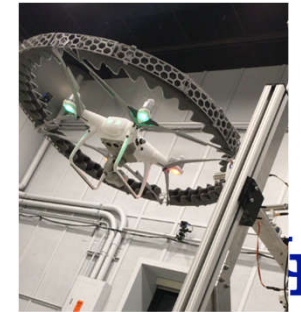
Parker 54



Bonner 126

Acoustic Field Characterization

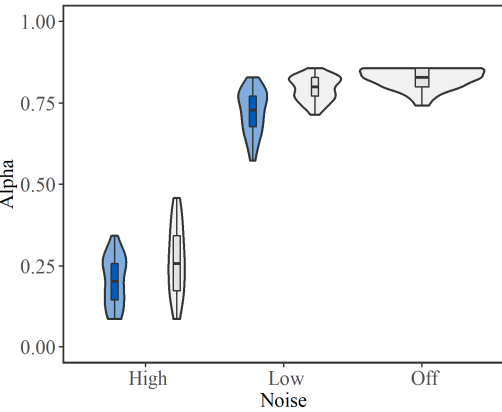
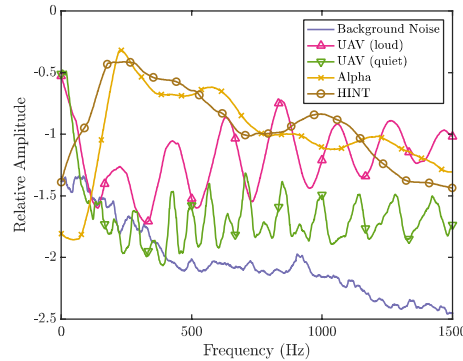
Materials Testing & Drone Re-design



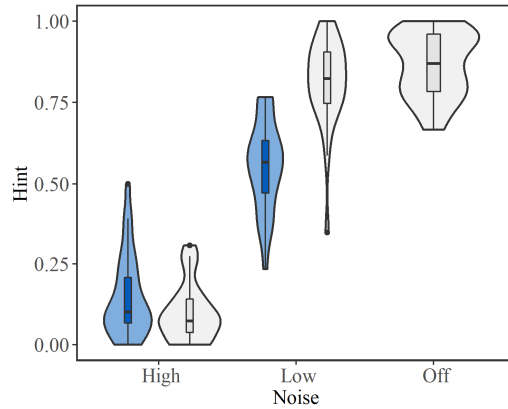
Human Factor Experiments

➤ Participants

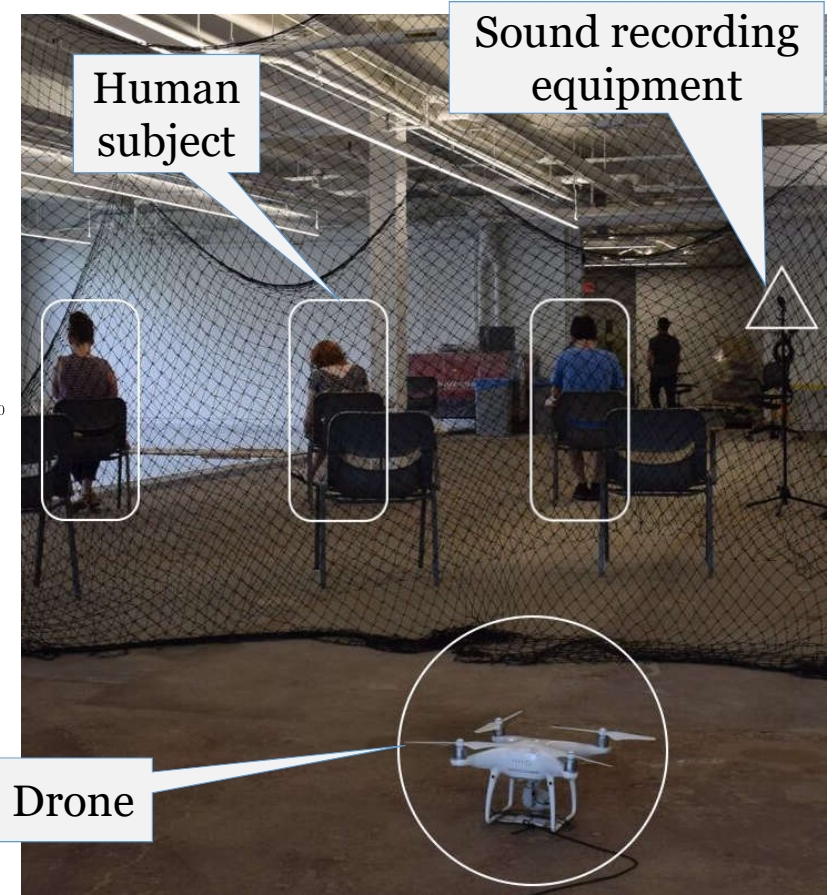
30 volunteers recruited for participation
 Each participate in two hearing and reproduction tests.



Distance
 Far
 Near



The source noise level was found to have the most significant impact

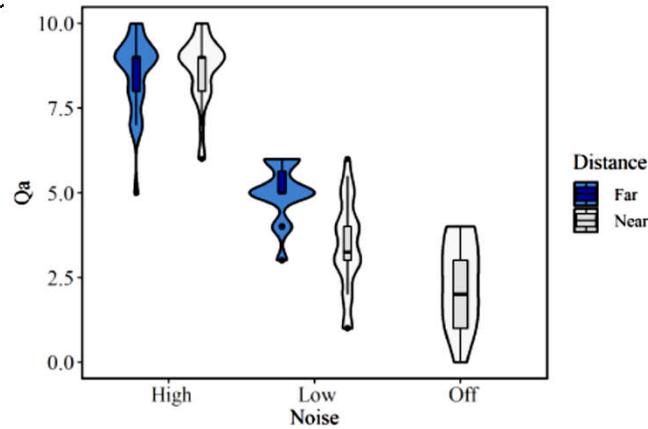


Anybody Interested to participate in the next round of experiments? We will be taking brain EEG measurements as well (pretty cool huh 😊)

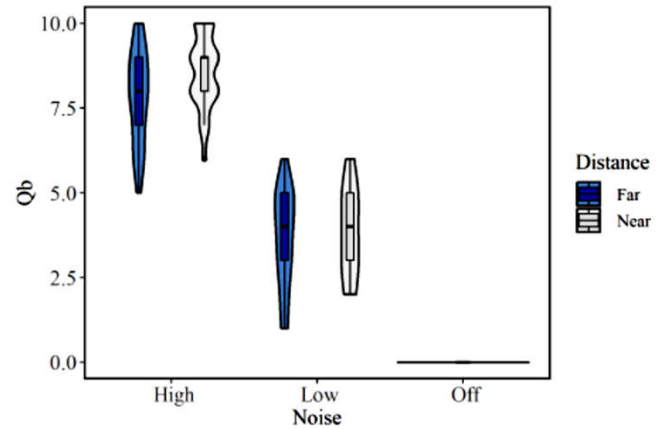
Flood Simulation Details

- The flood in this scenario is set to a very aggressive rate of rise of nearly 4m per hour. This is comparable to extreme flash flooding scenarios that have been recorded following the breaking of levees or dams upstream [44, 45].
- There are two flood water levels; the first level is a horizontal plane, which starts at the elevation of the ocean water and rises uniformly at a user defined rate (4 meters per hour); the second level is an inclined plane underneath the river drainage of Hilo, where water level rises at an averaged rate of 6 meters per hour;
- Water does not recede during the mission (a flooded area remains flooded).

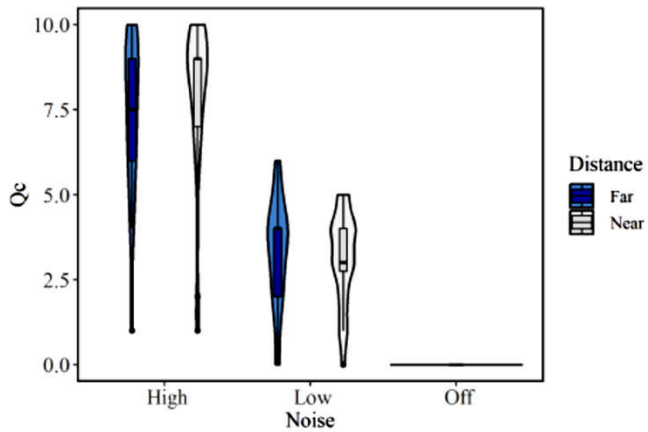
Human Factor Experiments



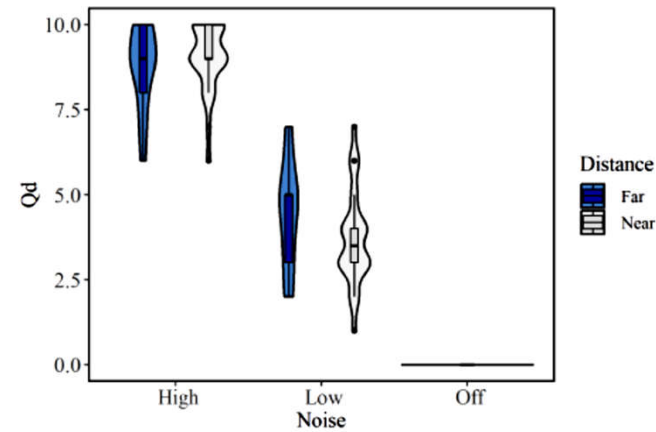
(a) Qa: the difficulty of hearing/understanding the voice.



(b) Qb: the loudness of UAV noise.



(c) Qc: the degree to which the UAV noise was annoying/irritating for you.



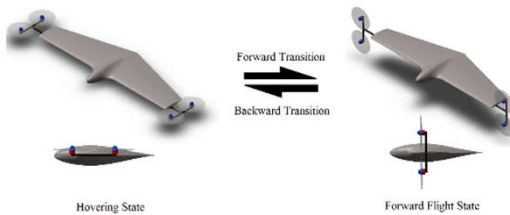
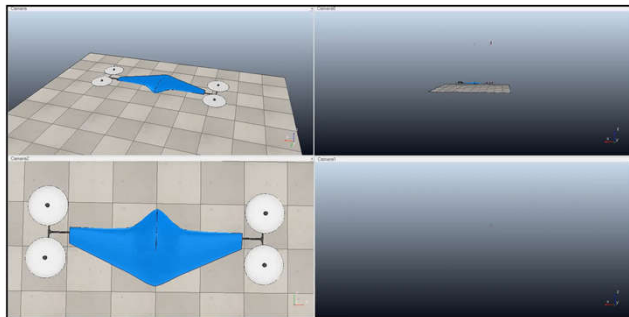
(d) Qd: the degree to which the UAV noise affected your ability to listen to the voice.

Questionnaire
feedback

Conceptual Design of a Hybrid UAV

Our Solution -- Hybrid UAV that transitions between Hover/VTOL/Long-Range Flight.

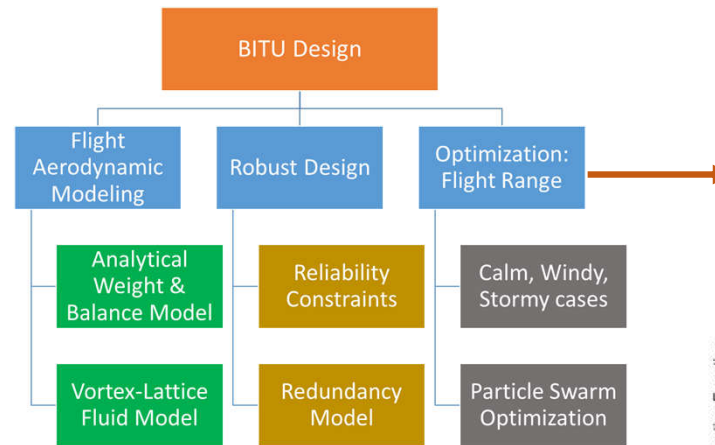
Standard Drones
 Unsuitable for demanding humanitarian missions
 NO hovering or VTOL



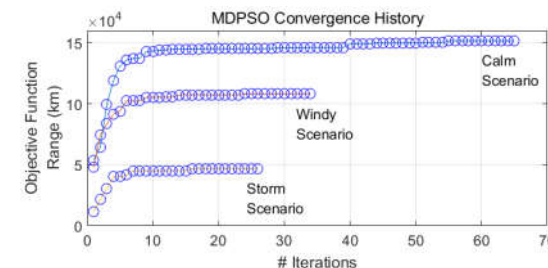
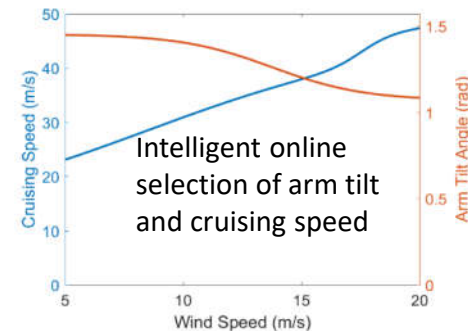
BWB-Integrated Transitioning UAV

- Zeng, C., Behjat, A., and Chowdhury S., *Uncertainty-aware Optimal Flight State Selection for a Transitioning UAV via Simulation-based Learning*, AIAA Aviation, Atlanta, Georgia, June 25-29, 2018.
- Zeng, C., Abnous, R., Chowdhury, S. *Aerodynamic Modeling and Optimization of a Blended-Wing-Body Transitioning UAV*, AIAA Aviation, Denver, Colorado, 5 – 9 June 2017.

Property	DJI Matrice 200 (Multirotor)	X-UAV "Xiaoni" (Fixed-wing)	IAI Mini-Panther (Hybrid UAV)	BITU Prototype (optimized)
Size (Wingspan)	0.716 m	2.20 m	3.00 m	2.50 ~ 3.30 m
MTOW	6.14 kg	12.0 kg	12.0 kg	8.5 kg
Flight Range	20 km	200 km	50 km	120 km
Hover Endurance	24 min	N/A	N/A	25 min



Dynamics and Control model under development



UAV Design & Autonomy: Concluding Remarks

- The **performance** and **behavior** of UAVs are strongly **coupled**.
- **New UAV configuration concepts** have been designed, allowing long range flight with VTOL and hover capabilities.
- **Mutually reciprocal collision avoidance** schemes have been developed by synergizing optimization and **evolutionary neural systems**.
- While separate contributions have been made to physical design and behavior design of UAVs and testing in simulation environment, going ahead, we aim to
 - Efficiently model how the UAV body impacts learning – to enable a concurrent body/brain design approach.
 - Perform real-world testing of these concepts with flight experiments.

Complex System Design

(multi-fidelity modeling & optimization)



Bio-inspired AI

(Neuroevolution and Artificial Life algorithm: autonomy & co-design)



Swarm Systems

(Graph Theoretic, MILP, Swarm Heuristics for UAV and UGV swarm systems)

Complex System Design

(multi-fidelity modeling & optimization)



Bio-inspired AI

(Neuroevolution and Artificial Life algorithm: autonomy & co-design)



Swarm Systems

(Graph Theoretic, MILP, Swarm Heuristics for UAV and UGV swarm systems)

Methodology Assumptions & constraints

- Movement of Quadrotor is idealized
 - No uncertainty in movement
 - No considerations for underlying flight dynamics
- Negligible weather effects
 - Static wind conditions
 - Stationary oil spill
- No Continuous Video
 - 5 second image sampling rate
- Limited Endurance
 - Quadrotors only have a range of 40 km

Property	Value
Range	40 km (Round Trip)
Field of View	100 m ²
Max Velocity	60 km/hr
Repulsion Range	10 m
Turning Radius	0 (Instant Turning)