Toward Infinitely Scalable Robotic Swarms

Melanie E. Moses
Associate Professor of Computer Science & Biology
University of New Mexico
External Faculty, Santa Fe Institute

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Complex Systems Summer School

https://www.youtube.com/watch?v=ye5F9_03z0g

NASA Swarmathon

THE UNIVERSITY of NEW MEXICO

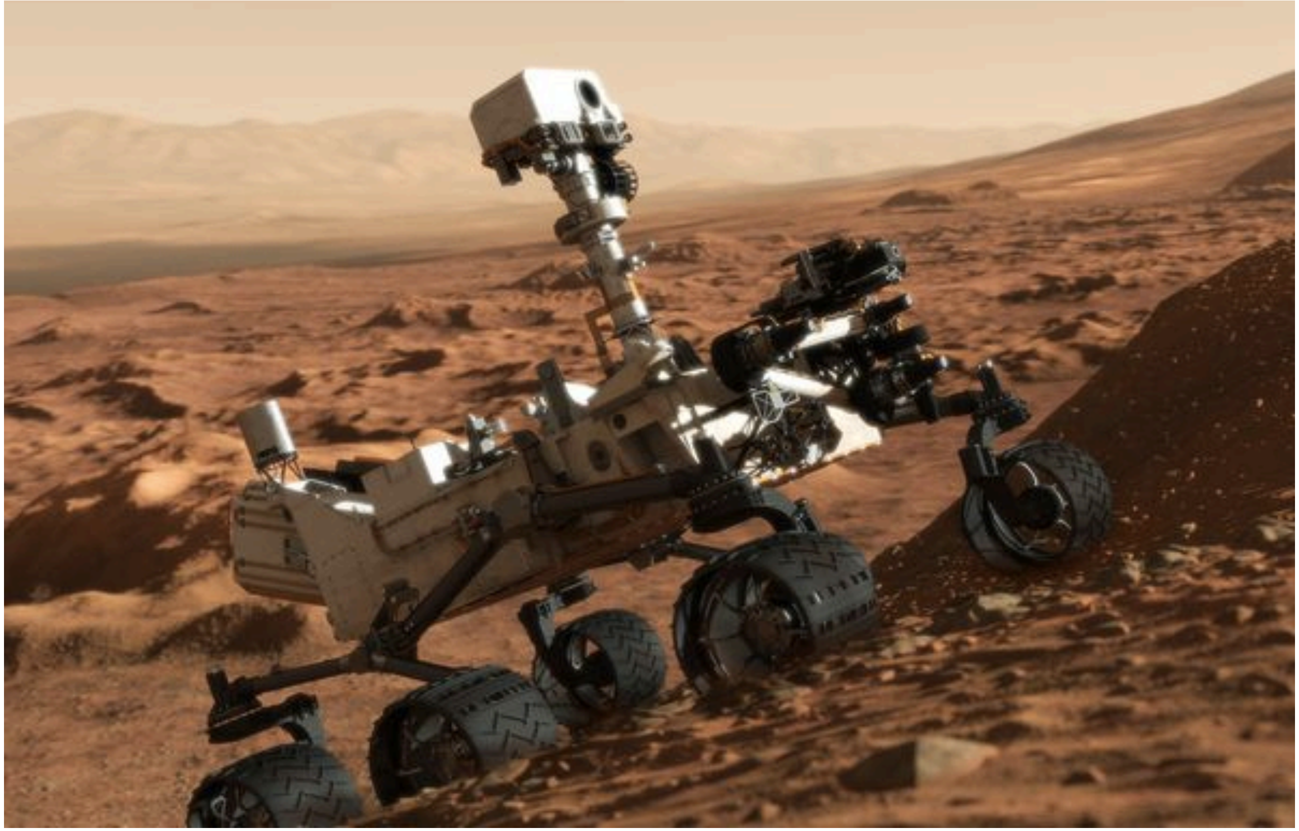
Autonomous Navigation

Autopilot

Fully Autonomous Car

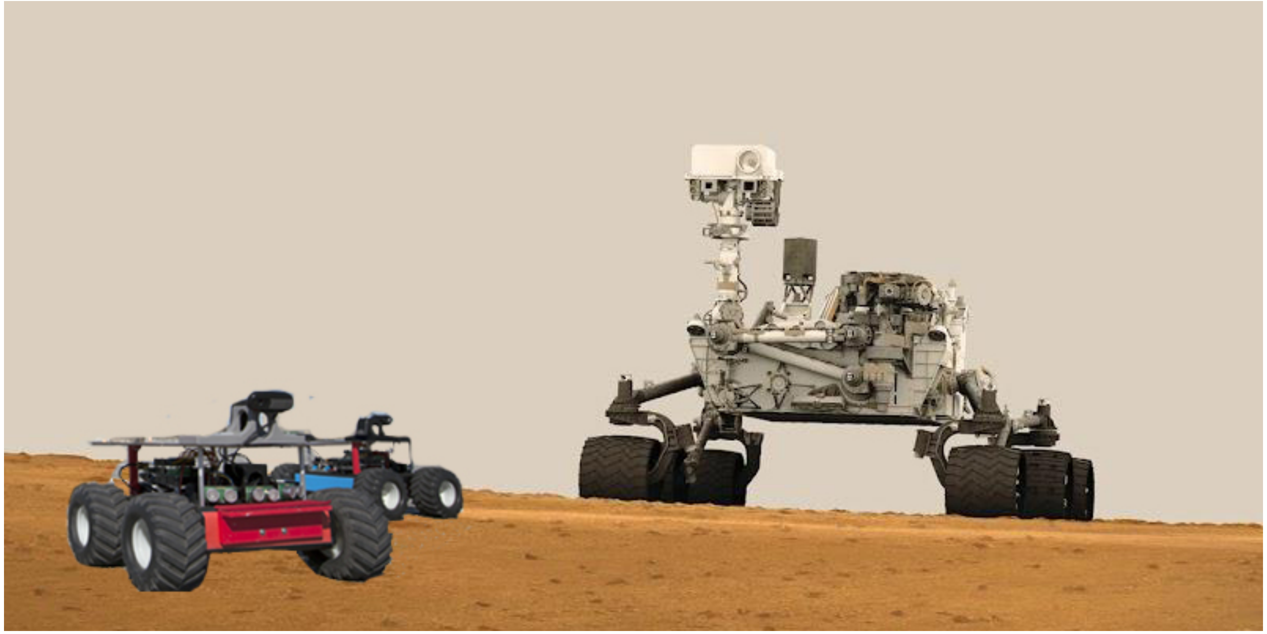
Autonomous Navigation

Remote control from earth is very slow



NASA'S Mars Curiosity Debuts
Autonomous Navigation & Autonomous Targeting!

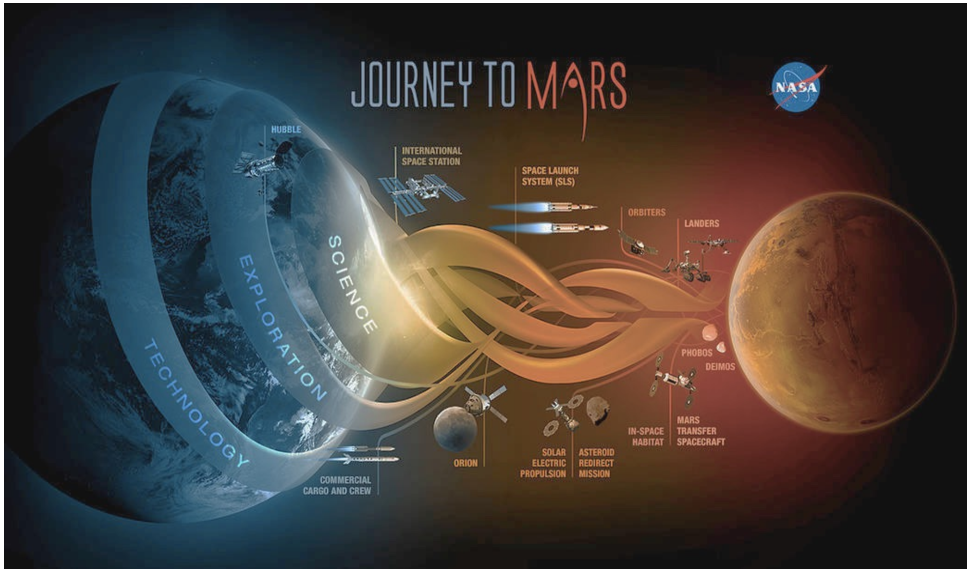
Autonomous Swarms are much faster

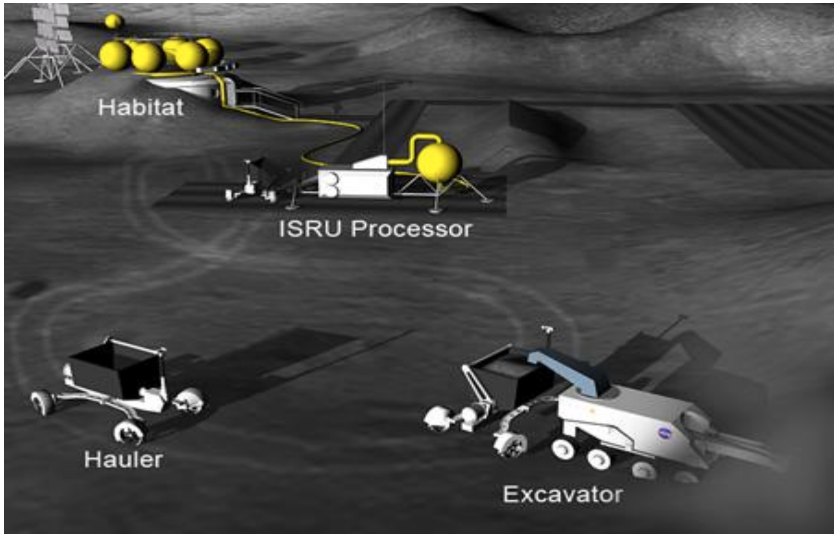


A swarm of 40 robots could travel 26 miles in 1 day
The Opportunity Rover travelled 26 miles in 11 years

Swarms provide scalability, robustness & flexibility

Autonomous Resource Collection
Living off the land

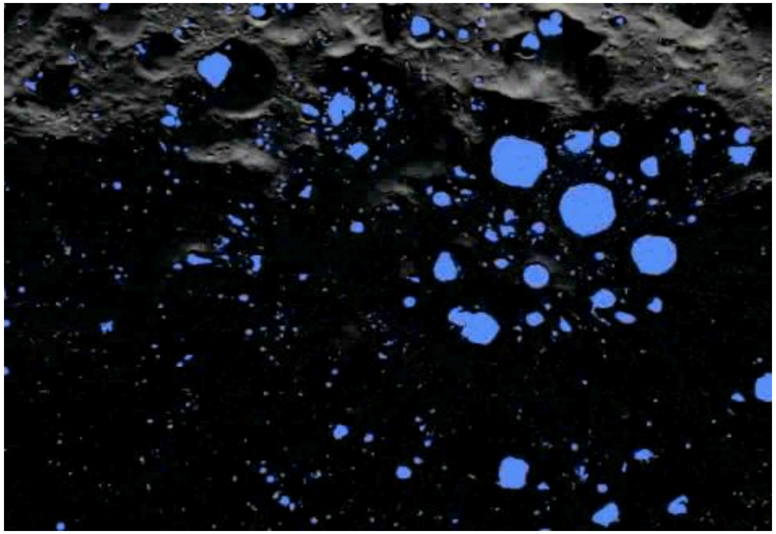




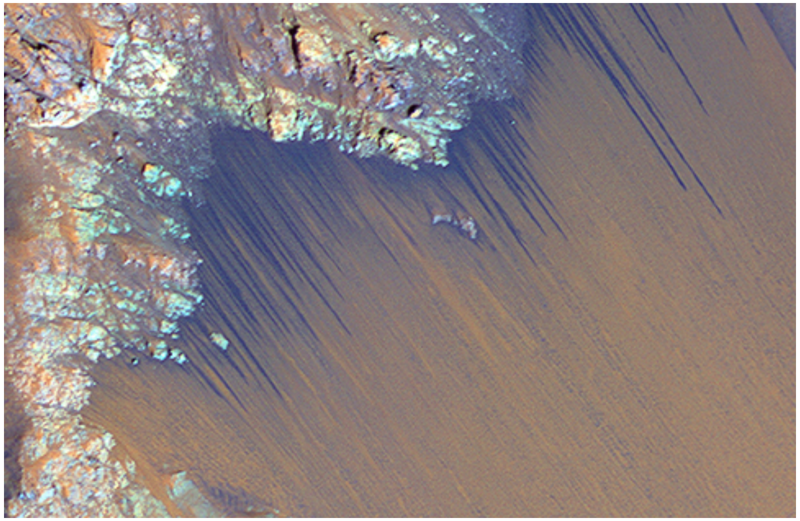
NASA's Journey to Mars will send robots to collect resources needed for astronauts to survive on the Martian surface

Autonomous Resource Collection

Living off the land



Ice on the moon



Ephemeral water on Mars

Rocks & Minerals on Mars

From Biological Inspiration to Robust, Flexible & Scalable Foraging Robot Swarms

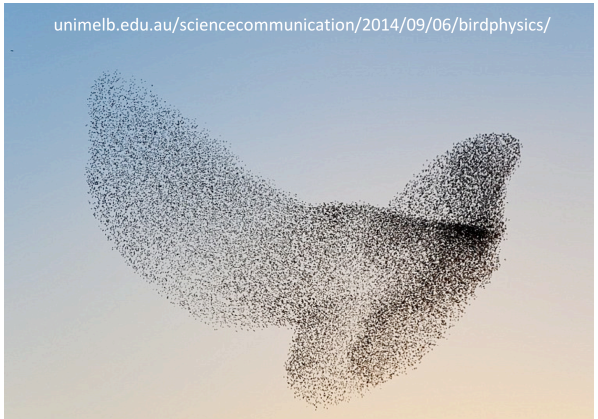
- **Biologically Inspired Swarms**

- **CPFA: Evolving a Robust, Flexible & Scalable Foraging Algorithm inspired by ants**

- **CPFA extensions and the (infinitely?) scalable MPFA**

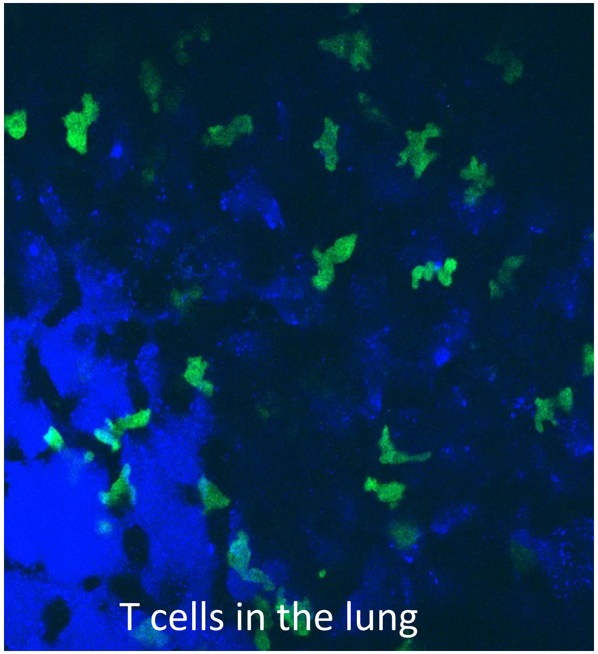
NASA Swarmathon

Swarms in Biology



Decentralized Control

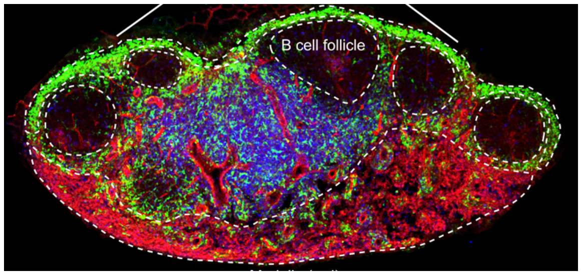
Collective behaviors emerge from interactions among individuals



Efficient for spatially distributed search

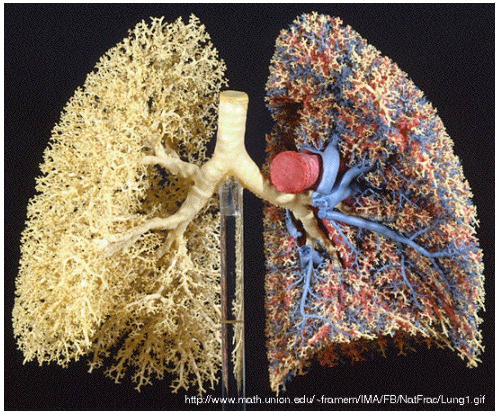
Robust, Flexible & Scalable

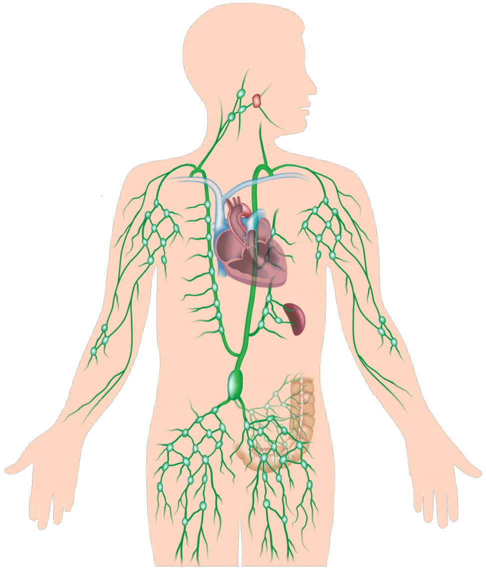
Immune cell "swarms" demonstrate Flexibility Across Environments and Scalability to trillions of cells

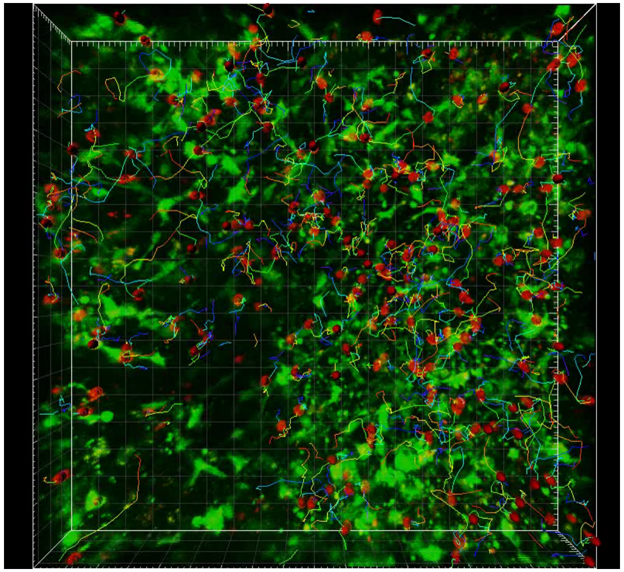


lymph node

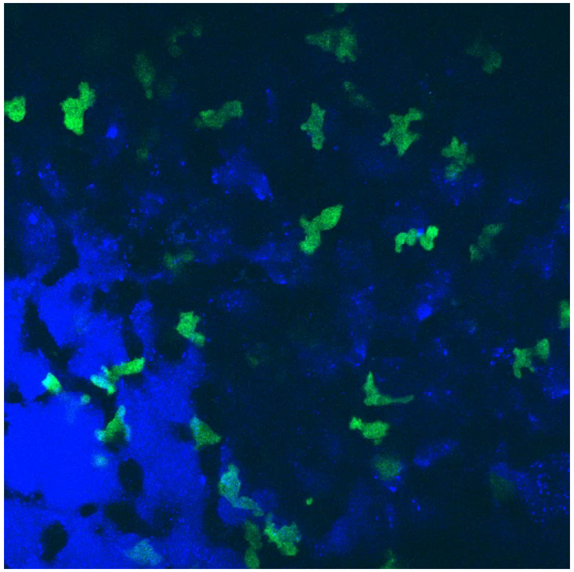
T cells search for pathogens in lymph nodes, lungs, reprod. tract, blood vessels…







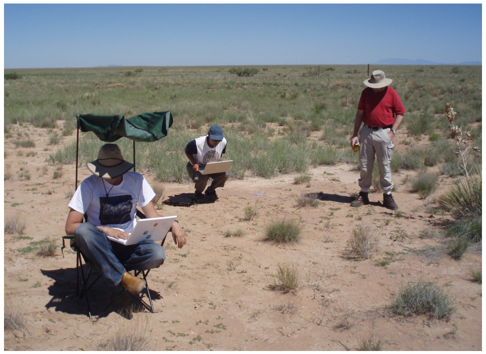
Each organ is a different environment with different movement and communication

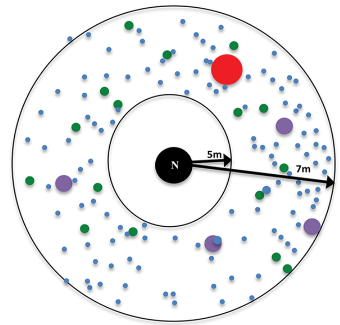


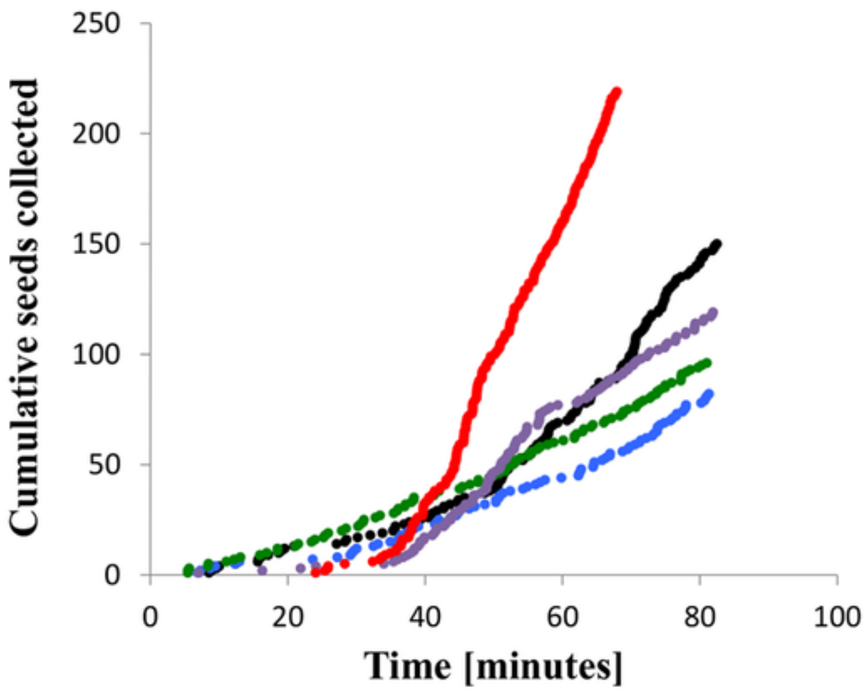
Flexibility Across Environments
Scalability to Millions of Ants

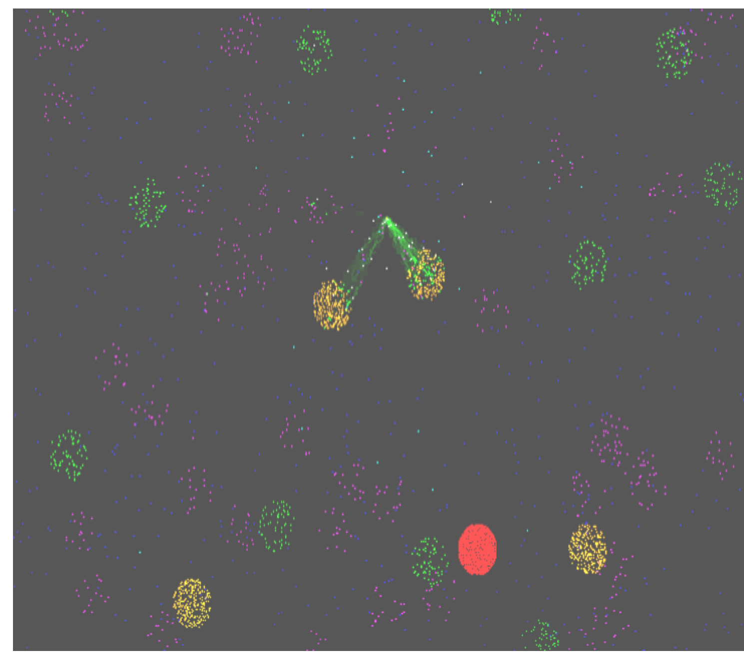
14,000 ant species in diverse habitats across earth's ecosystems

Central Place Foraging in Desert Ants







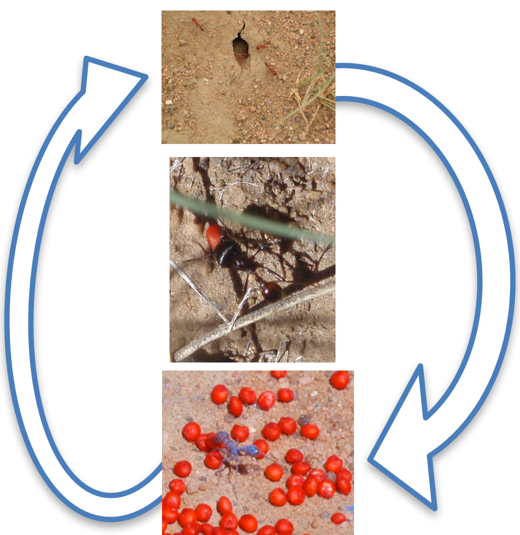


[Flanagan 2011, 2013; Letendre 2013]

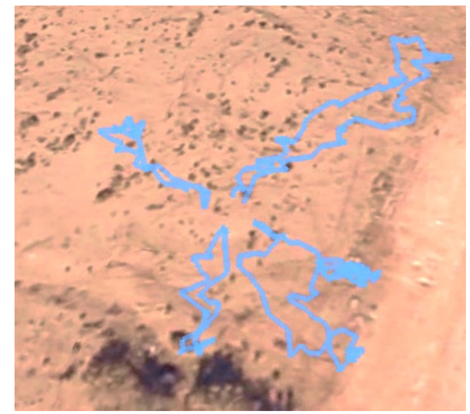
Scalable, Flexible, Robust Foraging from a simple repertoire of behaviors

Assess seed pile density
Count Targets (assess density)

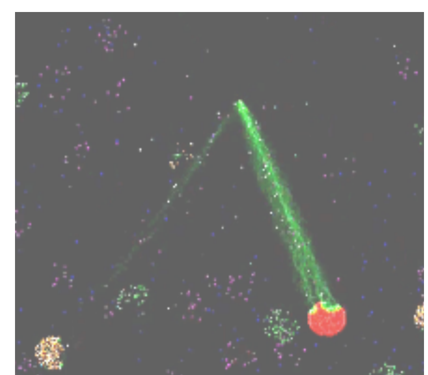
Remember & Return to seed piles
Site Fidelity



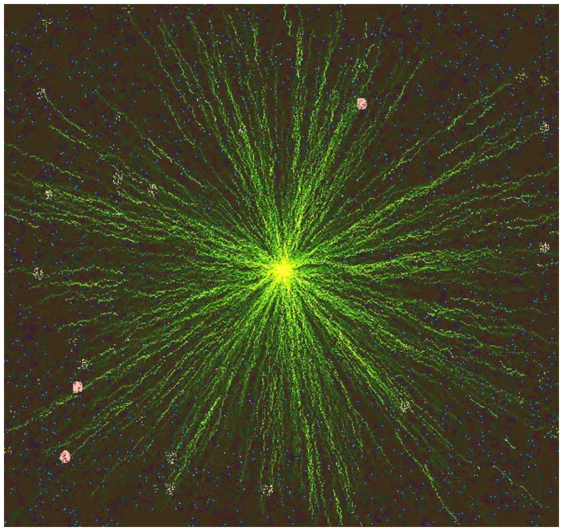
Movement balances search thoroughness vs extent
Correlated Random Walk



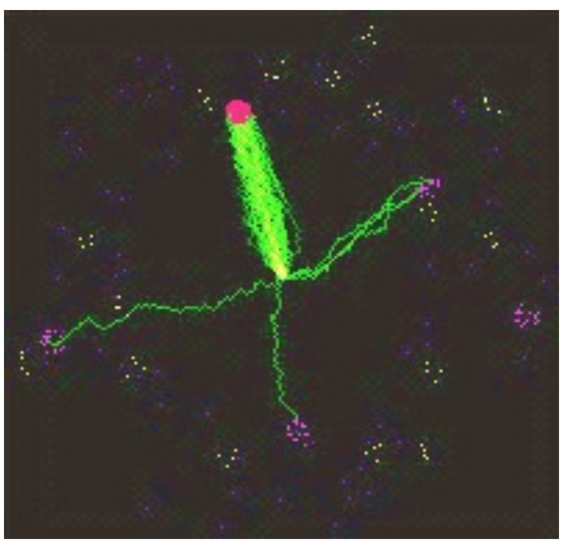
Communicate
Pheromones

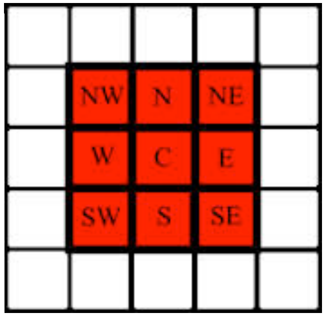


Foraging success depends on Interactions among behaviors & environment



Lay pheromone
Whenever I find a seed



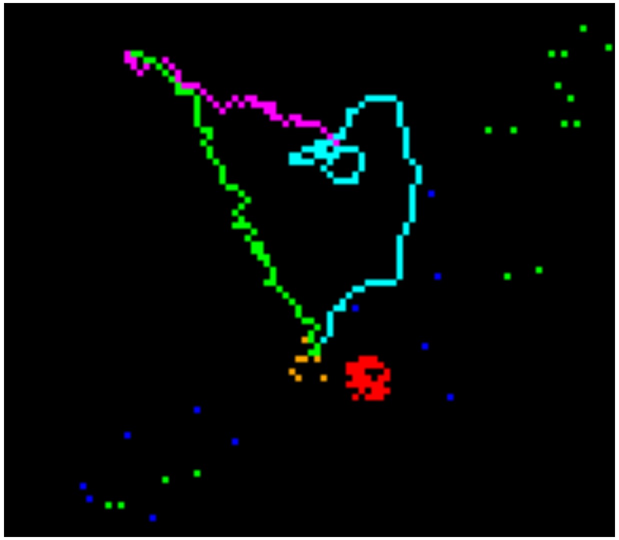


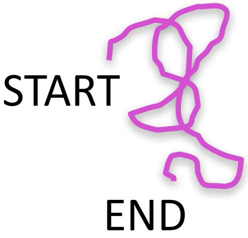
Lay pheromone
Only if count > 5

Appropriate communication depends on what is sensed in the environment

Foraging success depends on interactions among behaviors & environment

Movement balances the extensiveness and thoroughness of search





Informed Walk

After returning via site fidelity or following a pheromone trail
Turn often to search thoroughly

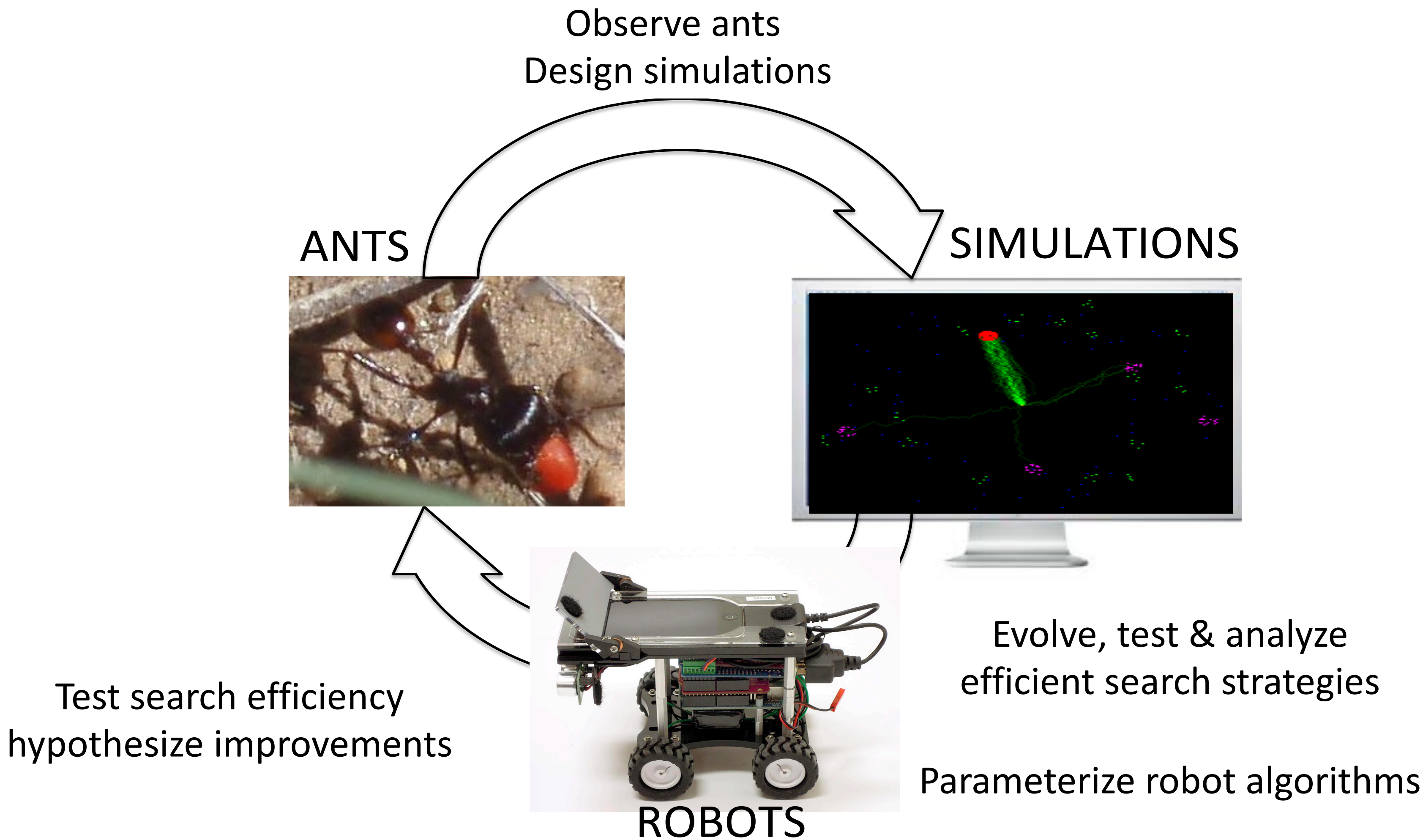
Uninformed Walk

When searching at random,
walk straight to search widely

Appropriate movement depends on what has been communicated & remembered

From Biological Inspiration to Robust, Flexible & Scalable Foraging Robot Swarms

- **Biologically Inspired Swarms**
- **CPFA: Evolving a Robust, Flexible & Scalable Foraging Algorithm inspired by ants**
- **CPFA extensions and the (infinitely?) scalable MPFA**



“Go to the ants thou sluggard, consider her ways and be wise.”

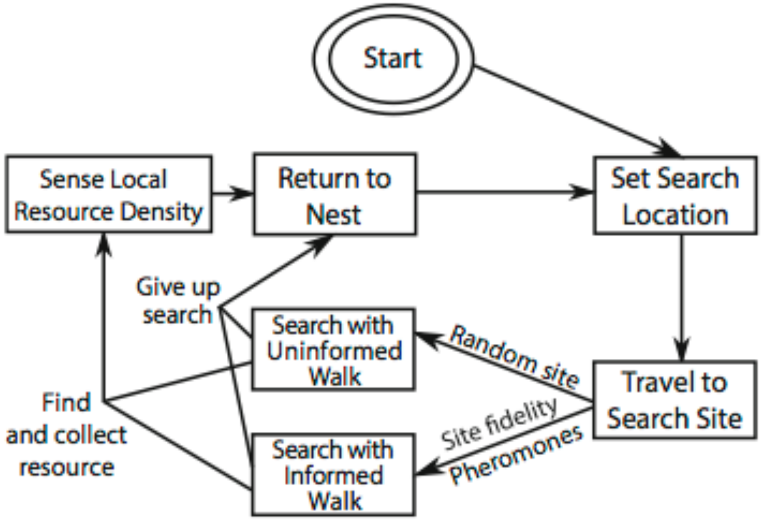
- Proverbs 6:6

Central Place Foraging Algorithm (CPFA)

Parameter	Description	Initialization Function
p_s	Probability of switching to searching	$\mathcal{U}(0,1)$
p_r	Probability of returning to nest	$\mathcal{U}(0,1)$
ω	Uninformed search variation	$\mathcal{U}(0,4\pi)$
λ_{id}	Rate of informed search decay	$exp(5)$
λ_{sf}	Rate of site fidelity	$\mathcal{U}(0,20)$
λ_{lp}	Rate of laying pheromone	$\mathcal{U}(0,20)$
λ_{pd}	Rate of pheromone decay	$exp(10)$

7 parameters govern

- movement
- counting
- communication
- memory



[Hecker & Moses *Swarm Intelligence* 2015]

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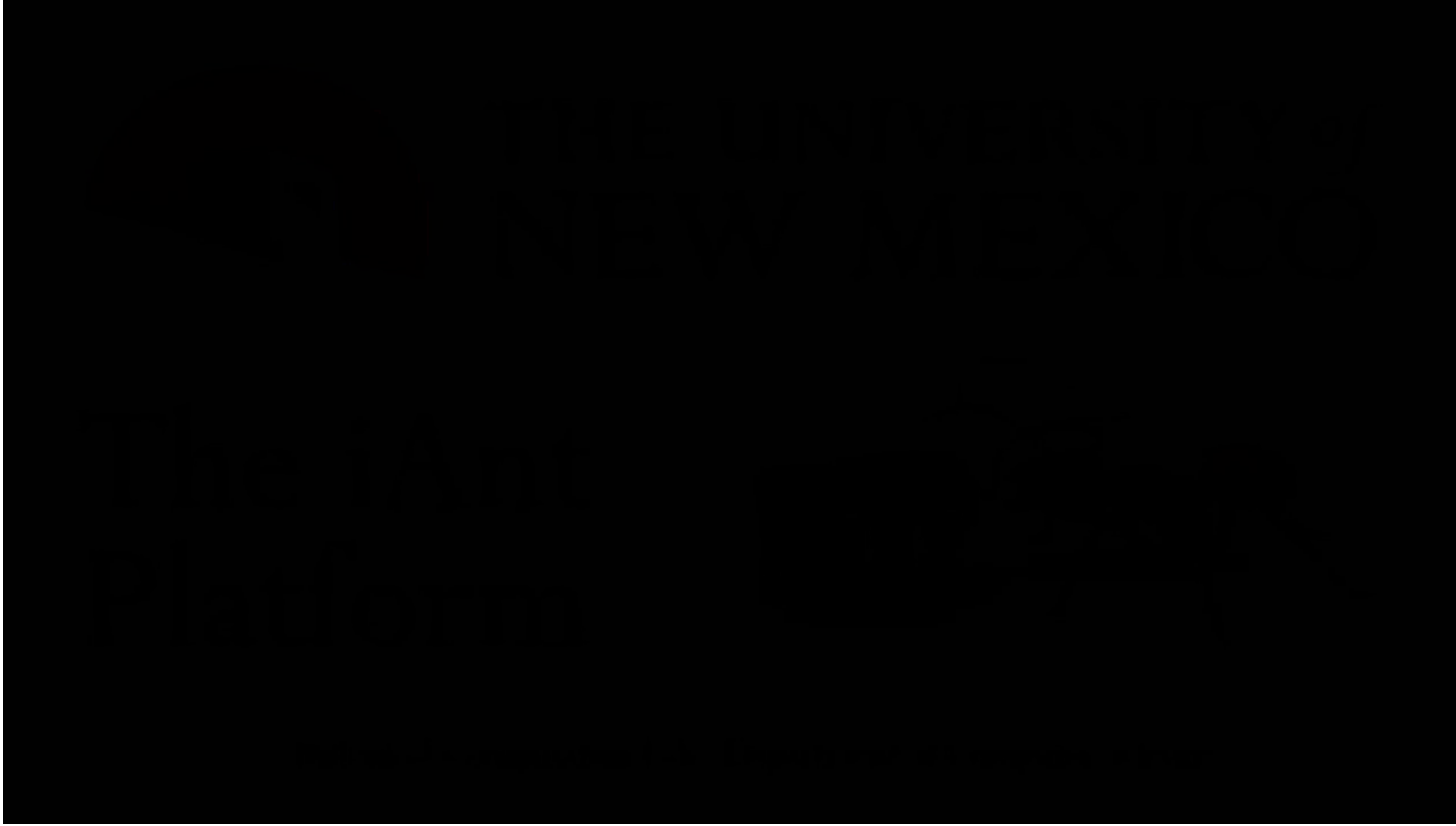
λ_{pd}	Rate of pheromone decay	$exp(10)$

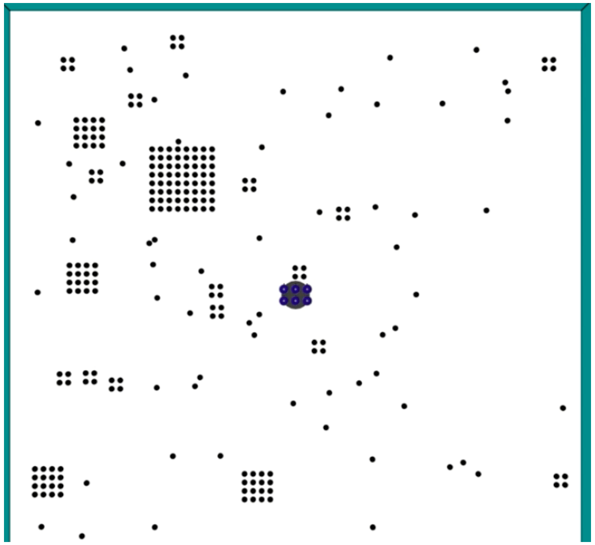
- Uninformed robots use a Correlated Random Walk: $\theta_t = \mathcal{N}(\theta_{t-1}, \omega)$
- Informed robots use a less correlated CRW: $\sigma = \omega + (4\pi - \omega)e^{-\lambda_{\mathrm{id}} t}$
- Information decisions governed by a Poisson CDF: $\textsc{Pois}(c,\lambda) = e^{-\lambda} \sum_{i=0}^{\lfloor c \rfloor} \frac{\lambda^i}{i!}$
  - Robots return to location of discovered resource if the count of nearby resources *c* is large
  - Robots can use memory (site fidelity, $\lambda = \lambda_{sf}$) or communication (pheromone-like waypoints, $\lambda = \lambda_{lp}$)
- Pheromone waypoints decay exponentially over time: $\gamma = e^{-\lambda_{pd} t}$



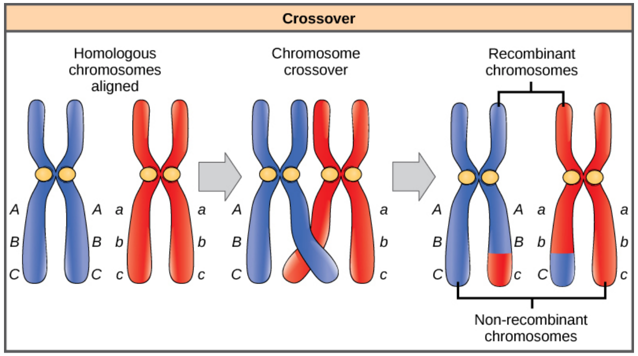
- Efficiently explore with correlated random walk
- Count resources by rotating 360°
- Return to resource piles via individual memory (site fidelity) or communication (pheromone waypoints)
- Movement, memory, and communication tuned by Genetic Algorithm

Genetic Algorithm selects CPFA parameters to maximize seeds collected in fixed time

In silico group selection evolves swarms that maximize foraging rate



- Simulate 1 hour of foraging with random tag placements in a specified distribution
- Simulate 100 swarms, each with its own CPFA parameter set [p_t, p_s, ω, λ_{id}, λ_{lp}, λ_{sf}, λ_{fp}]
- Swarms with highest "fitness"(tags collected in 1 hour) replicate to next generation



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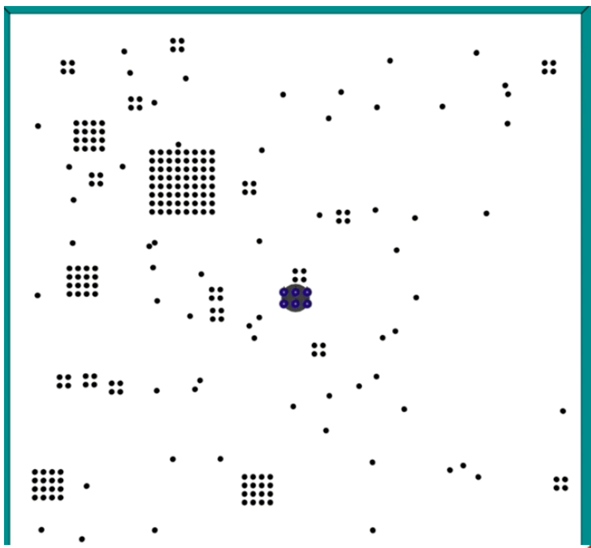

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- Swarms with highest “fitness”(tags collected in 1 hour) replicate to next generation

Mutate & recombine parameters

Repeat for 50 generations

$[p_t, p_s, \omega, \lambda_{id}, \lambda_{lp}, \lambda_{sf}, \lambda_{fp}]$ x $[p_t, p_s, \omega, \lambda_{id}, \lambda_{lp}, \lambda_{sf}, \lambda_{fp}]$

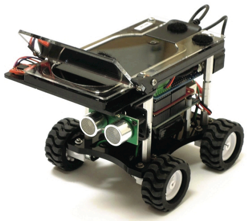
$[p_t, p_s, \omega, \lambda_{id}, \lambda_{lp}, \lambda_{sf}, \lambda_{fp}]$

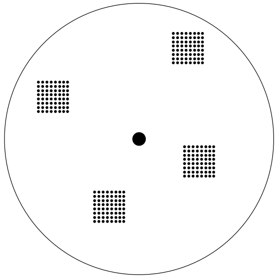
Each robot in the swarm has identical parameters evolved to maximize tag collection of the whole swarm

Simulated & Physical Robot Foraging Experimental Setup

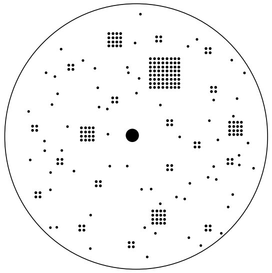
Experiments measure CPFA Flexibility, Robustness, Scalability in iAnts

- 6 robots per swarm, 256 tags, 1 hour in a 100 m^2 arena
- Simulations mimic measured robot detection & localization error
- Transfer evolved behaviors from simulation to physical robots
- Experimental results for 100 replicates in simulation, 10 replicates in robots

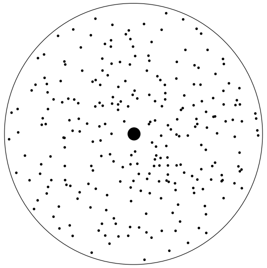




4 clusters



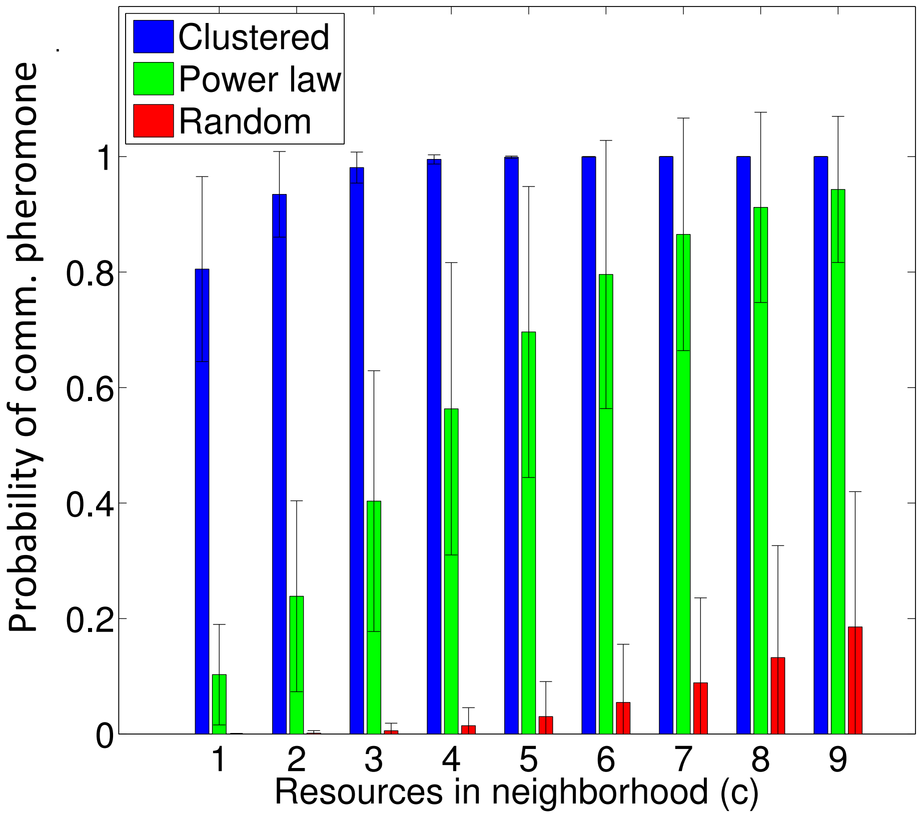
Partially-clustered

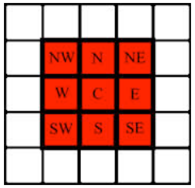


Uniform Random

Flexibility: different behaviors evolve for different target distributions

Communication evolves when resources are more clustered





[Hecker 2015]

Flexibility: different behaviors evolve for different target distributions

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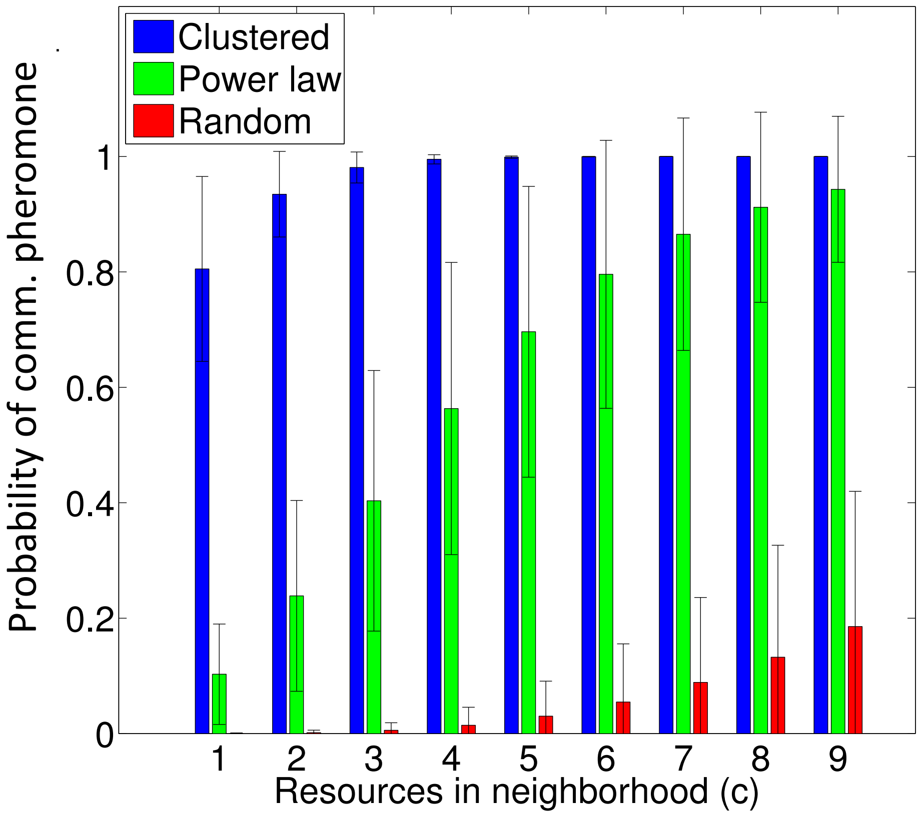
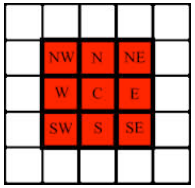
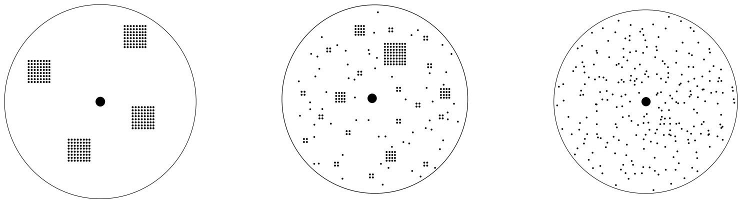




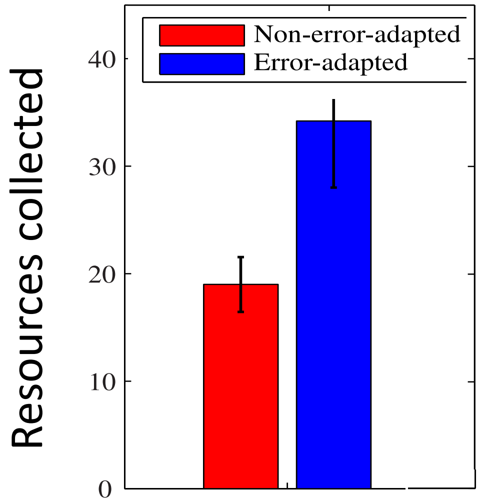
- Swarms evolve probability of using pheromone or site fidelity depending on the local resource count when they discover a tag



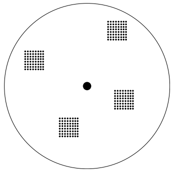
- Cluster-adapted swarms use more pheromone and less site fidelity
- Swarms adapted to partial clusters use less pheromone and more site fidelity
- Random-adapted swarms rarely use pheromones or site fidelity

[Hecker 2015]

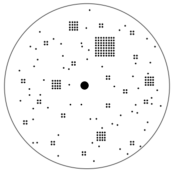
Robust & Flexible response to sensor error



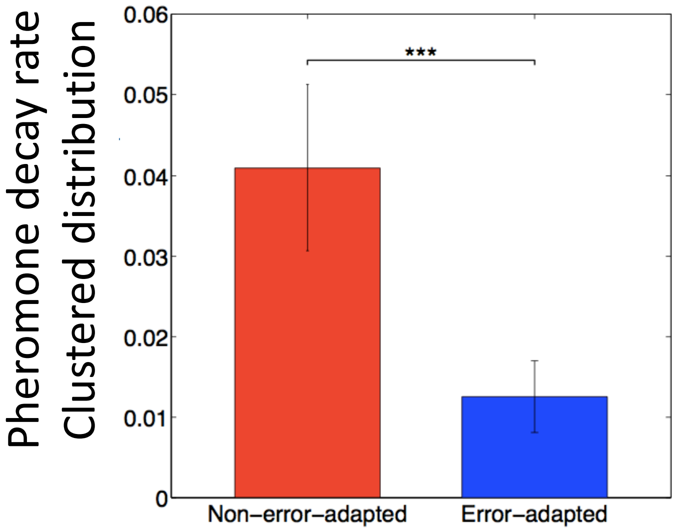
By evolving parameters that mitigate sensor error, robots collect twice as many resources

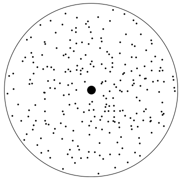


Robots evolved for clustered resources use more pheromone given error



For partially clustered resources, error causes robots to ignore pheromones and forage for dispersed resources

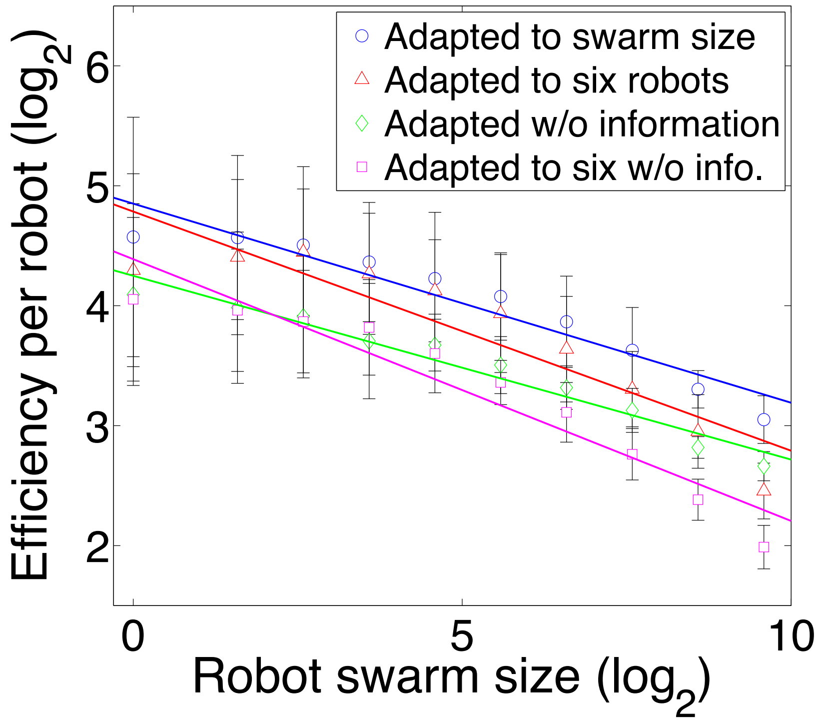




For randomly distributed targets, localization error is irrelevant

[Hecker2013, Hecker 2015]

CPFA has limited scalability



The CPFA adapts parameters to improve scalability, but central place foraging requires long travel times for large swarms collecting from large areas.

Summary of Results for the CPFA in iAnts

- Adaptable: different behaviors evolve to maximize tag collection from different resource distributions: more communication given larger piles.
- Flexible: in the partially clustered distribution the swarm balances use of site fidelity to collect from small piles and pheromone communication to recruit to large piles
- Robust: parameters evolve to mitigate sensor error, response dependent on tag distribution
- Scalable: parameters change systematically with swarm size (up to 768 simulated robots). Larger swarms disperse more and communicate less.

[Hecker2013, Hecker 2015]

From Biological Inspiration to Robust, Flexible & Scalable Foraging Robot Swarms

- Biologically Inspired Swarms
- CPFA: Evolving a Robust, Flexible & Scalable Foraging Algorithm inspired by ants
- **CPFA extensions and the (infinitely?) scalable MPFA**

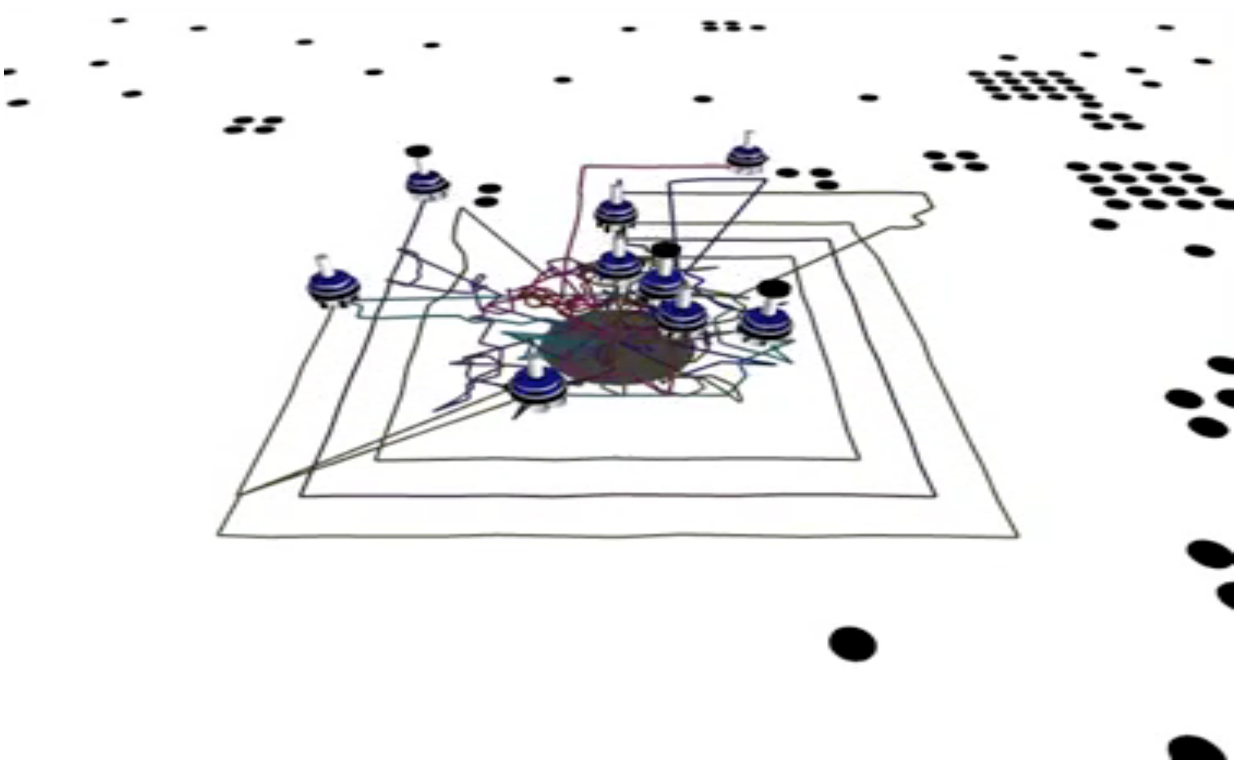
Scaling in CS

- How does computation time scale with input size?
- Example: Sorting Algorithms
  - https://www.toptal.com/developers/sorting-algorithms
  - Bubble Sort **$O(n^2)$**
  - Quick Sort **$O(n \log n)$**

Description	O-notation
constant	$O(1)$
logarithmic	$O(\log n)$
linear	$O(n)$
n log n	$O(n \log n)$
quadratic	$O(n^2)$
cubic	$O(n^3)$
polynomial	$O(n^k)$, $k \geq 1$
exponential	$O(a^n)$, $a > 1$

CPFA Extensions

Deterministic Distributed Spiral Algorithm (DDSA)
Efficient, Surprisingly Error Tolerant, Not Scalable



[Fricke 2016]

CPFA Extensions

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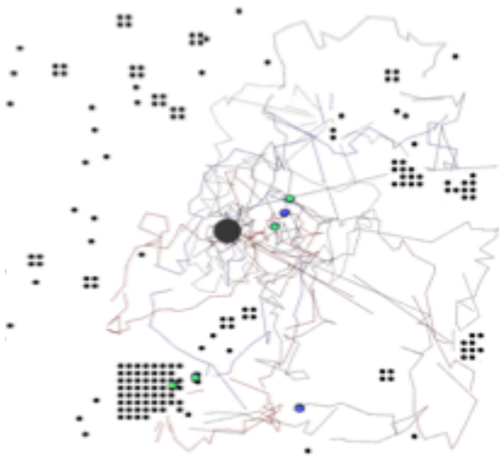
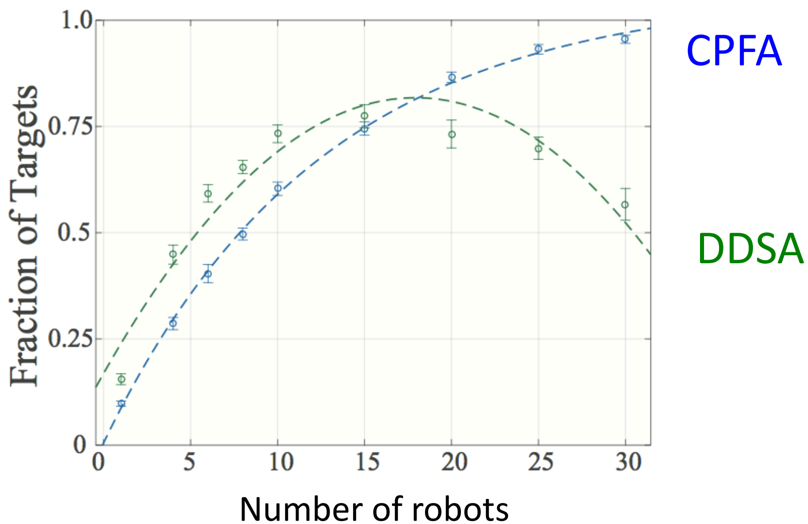


Noise coefficient: $e = 3.0$

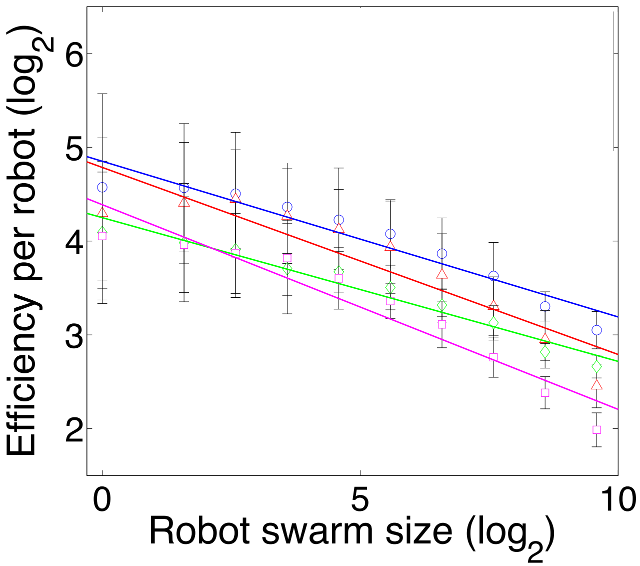


- The DDSA is 20% - 30% faster than the CPFA even with localization noise
- For complete collection, the DDSA is twice as fast as the CPFA
- DDSA is dramatically worse for large swarms

[Fricke IROS 2016]

CPFA Extensions

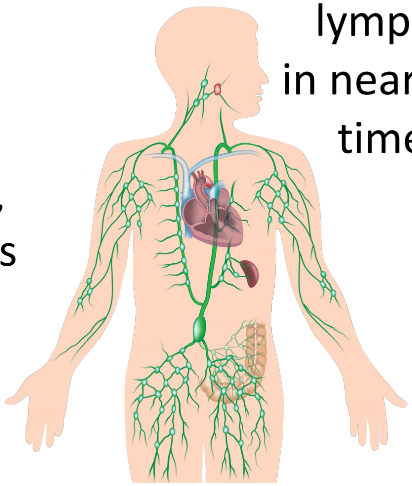
Improving Scalability with the Multi-Place Foraging Algorithm (MPFA)



Multi-nest "super colonies" of the invasive argentine ant span hundreds of kilometers

The CPFA adapts parameters to improve scalability, but central place foraging requires long travel times for large swarms collecting from large areas.

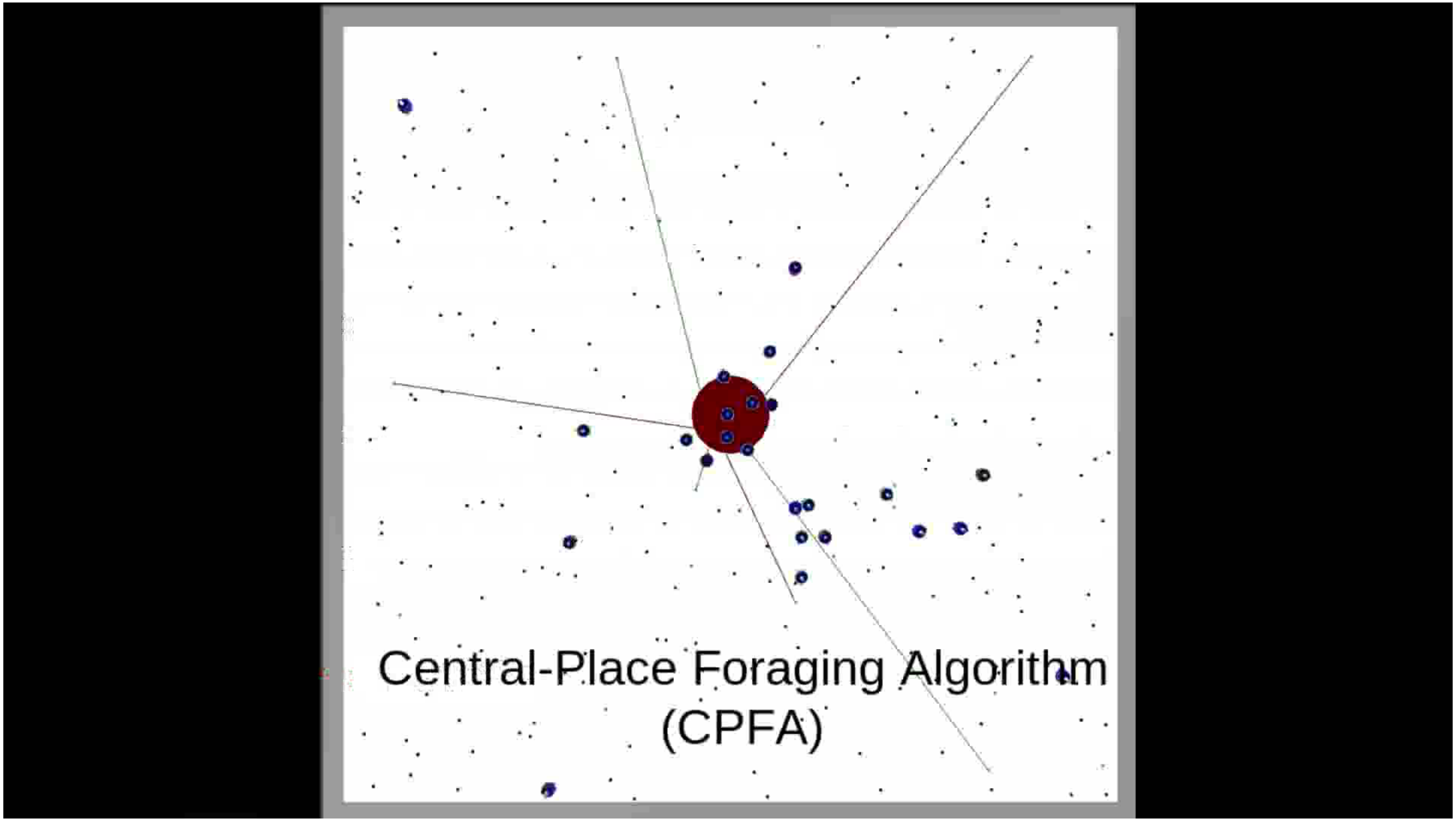
The MPFA mimics multi-nest ants & reduces travel time, collision time & search time in large swarms.



Modular, partially decentralized lymphatic network leads to in nearly scale invariant search time by trillions of T cells

[Lu IROS 2016]

MPFA



- $MPFA_{dynamic\_distributed}$

  https://drive.google.com/drive/folders/0B8V00V6njK2PVHNUNHBla0E2UjA

- $MPFA_{dynamic\text{-}central}$

  https://drive.google.com/drive/folders/0B8V00V6njK2PVHNUNHBla0E2UjA

- Robot Depot Design

https://www.youtube.com/watch?v=vu7QXRFIlj8&index=1&list=PLkjRv85y76xlLHEr0ekXVnVTy_z9TMZD4

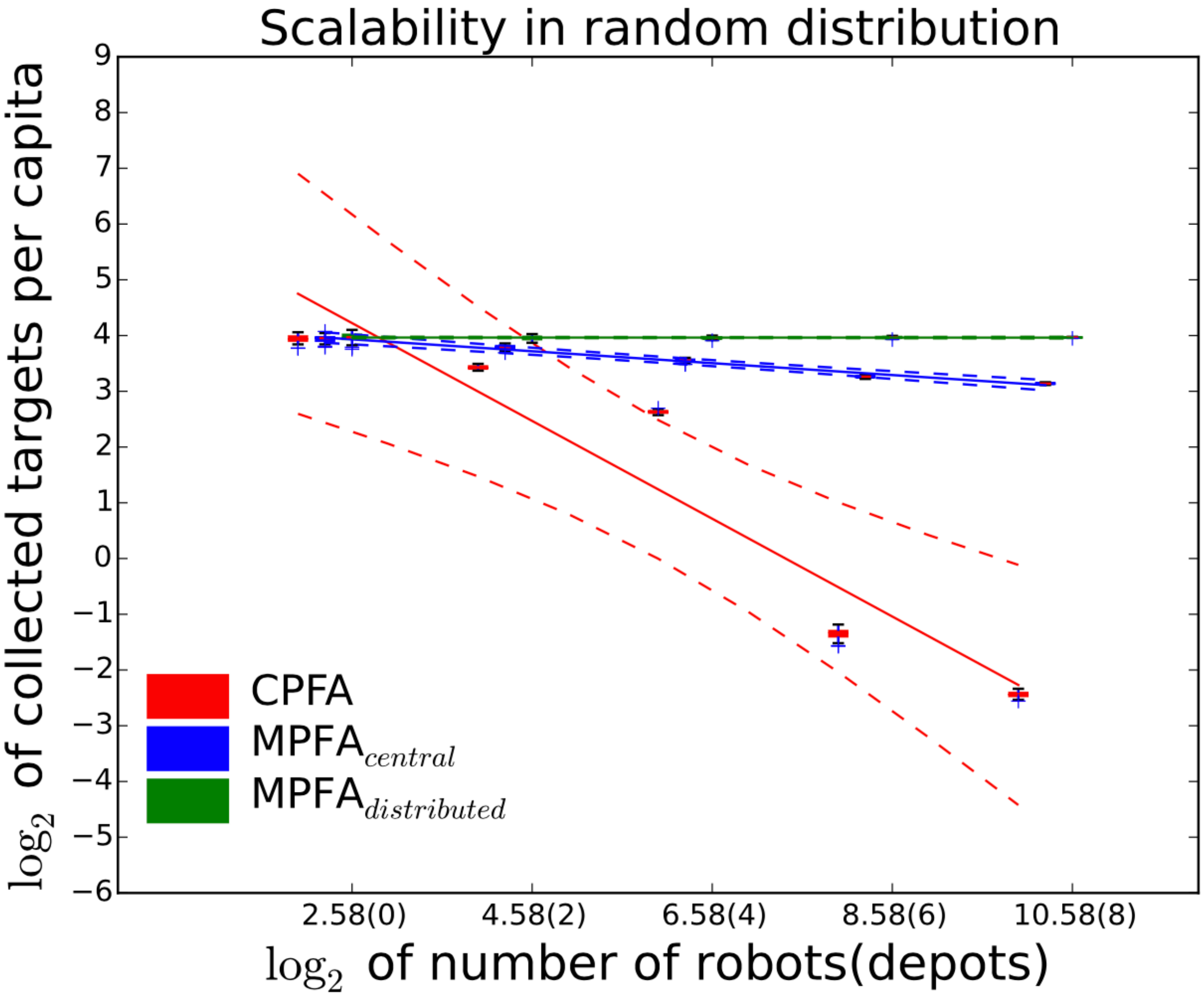


Fig. 5. The foraging efficiency of the CPFA, MPFA$_{central}$ and MPFA$_{distributed}$ in random distribution. Boxplots show original data of experiments. The three solid lines indicate linear regression on the $\log_2$ of collected targets per capita with the $\log_2$ of number of robots. The dashed lines indicate 95% confidence intervals ($slope = -0.88$, $slope = -0.11$, and $slope = -0.0003$, respectively).

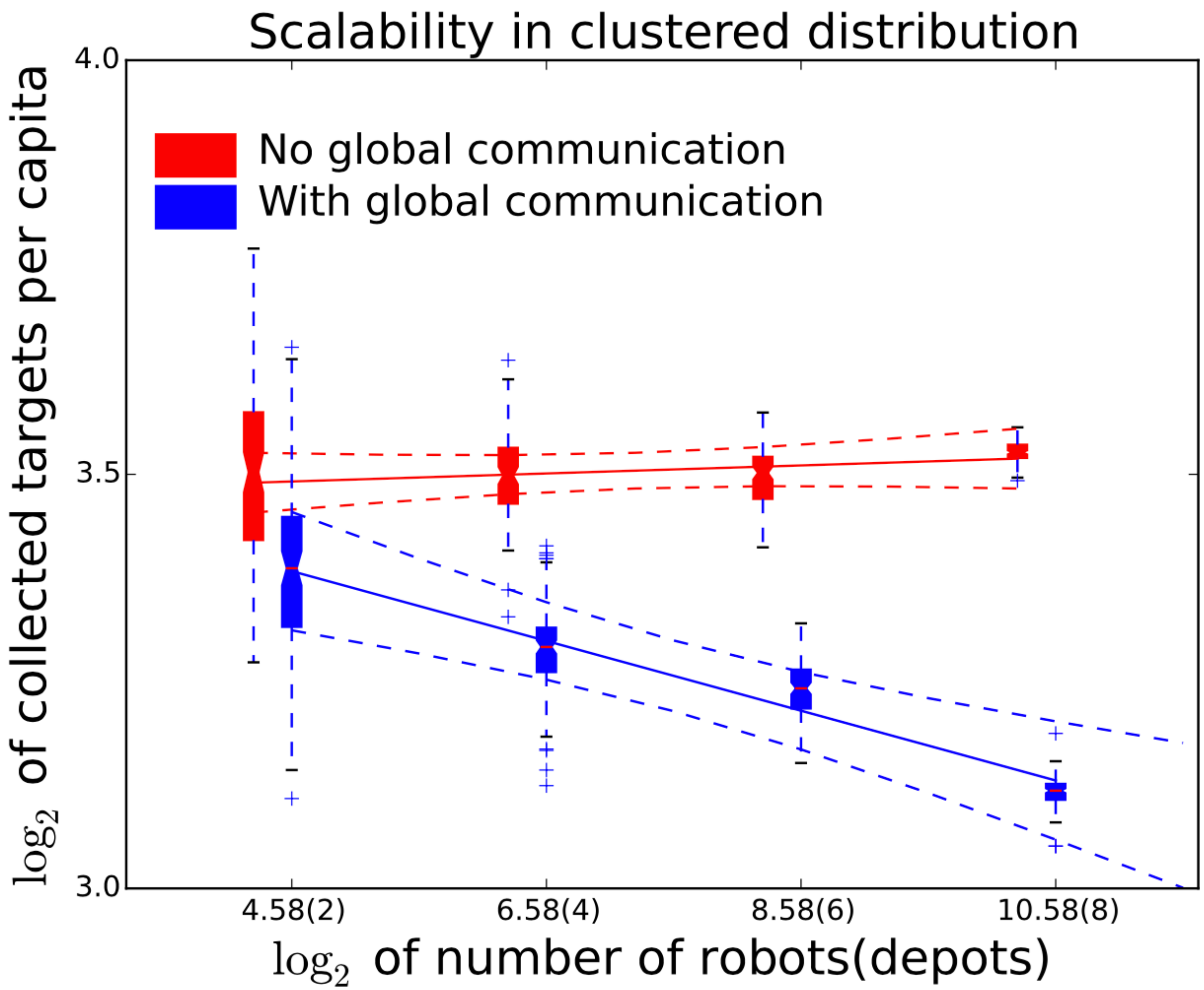
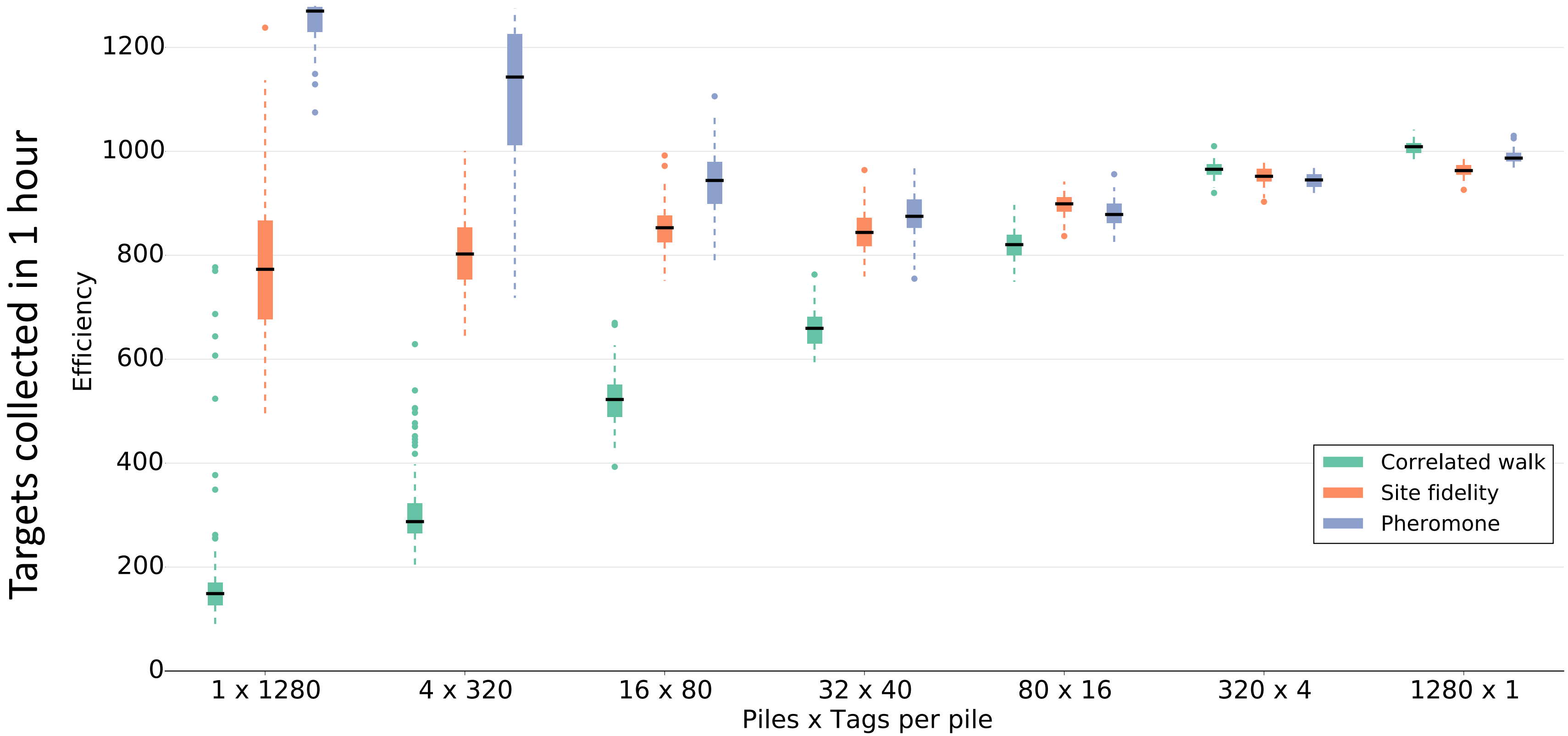


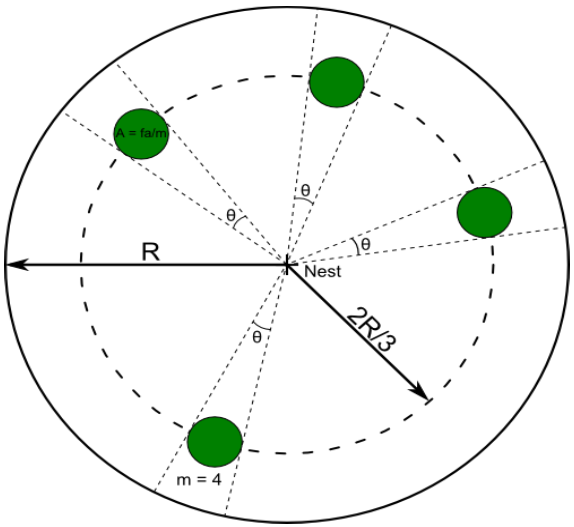
Fig. 8. The foraging performance per capita of the MPFA$_{distributed}$ with/without global communication in clustered distribution. Boxplots show original data of experiments. The two solid lines indicate linear regression on the log_2 of collected targets per capita with the log_2 of the number of robots. The dashed lines indicate 99% confidence intervals with/without global communication ($slope = 0.005$, and $slope = -0.04$, respectively).

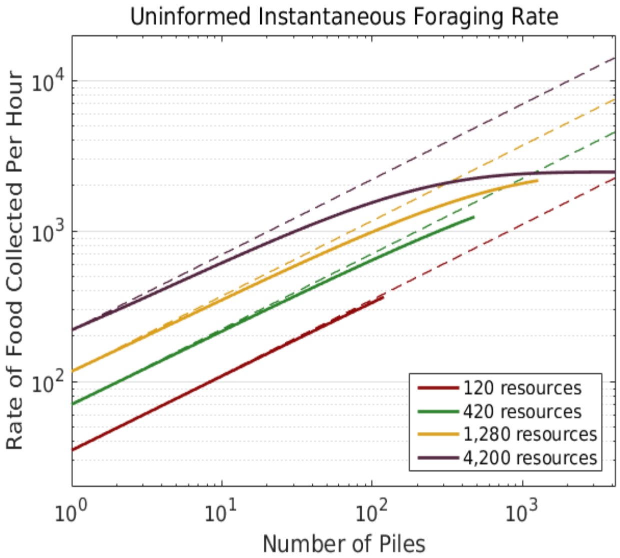
Information & communication improve search when targets are clustered in the CPFA



Joshua Hecker, unpub, UNM CS

Analytical Model of Random Foraging





Diameter of a Pile

$$d = 2\sqrt{\frac{fa}{m\pi}}$$

Angle of a Pile

$$\theta = 2sin^{-1}\left(\frac{3d}{4R}\right)$$

Probability of Hitting *At Least* One Pile

$$p = 1 - \left(\frac{2\pi - \theta}{2\pi}\right)^m$$

Expected Foraging Rate of *n* Ants

$$n \cdot \frac{df}{dt} = \frac{3nsp}{2R(3-p)}$$

Analytical Model of Nest Recruitment

Optimal Scout Population (x)

$$\frac{2k}{n-x} = \frac{2+q^x}{1-q^x}$$

Value of a Discovery:
Amount Able to be Collected

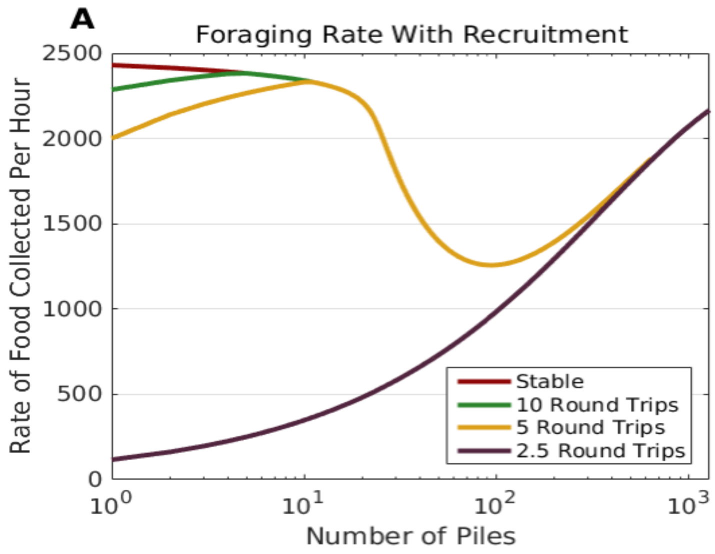
$$k = min\left(f/m - 1, \frac{(v-1)(n-x)}{2}\right)$$

Expected Foraging Rate of *n* Ants

$$n \cdot \frac{df}{dt} = \frac{3s[(n-x)(3-p)+2xp]}{4R(3-p)}$$

Value of nest recruitment

$$\frac{[(n-x)(3-p)+2xp]}{2np}$$



[Levin in prep]

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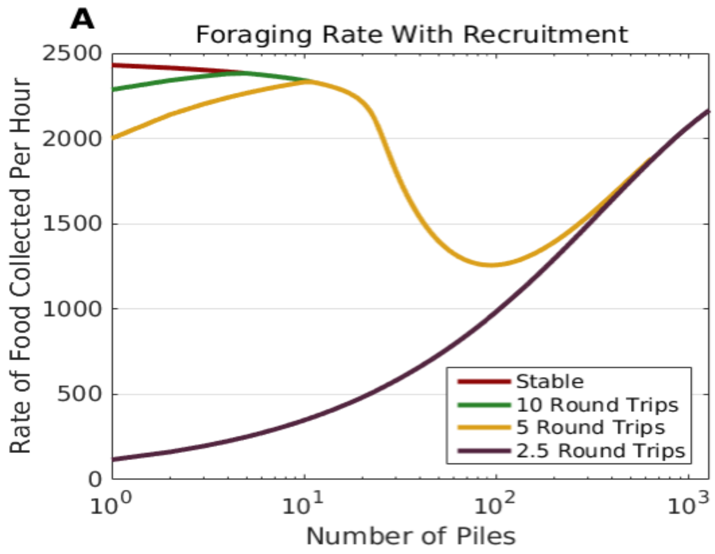

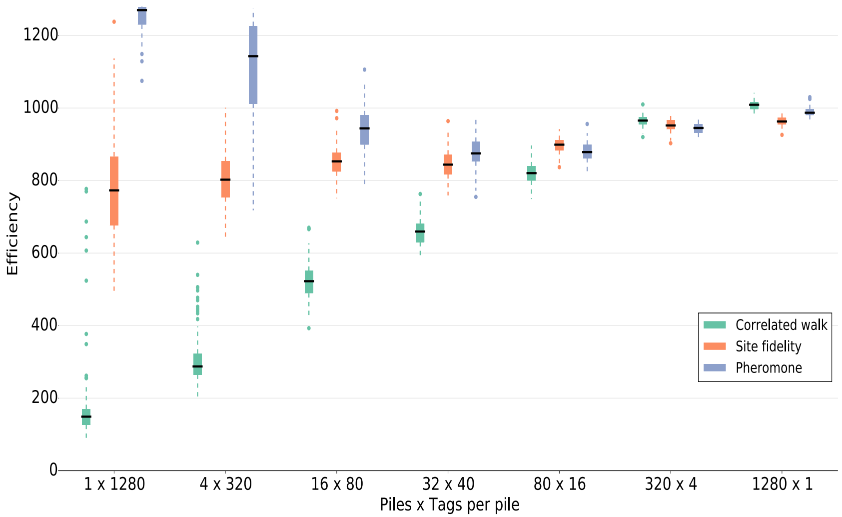

[Levin in prep]

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cs.unm.edu/~melaniem
NasaSwarmathon.com

Dr. Joshua Hecker

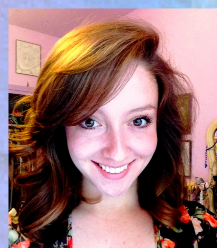
Dr. Kenneth Letendre

Karl Stollies

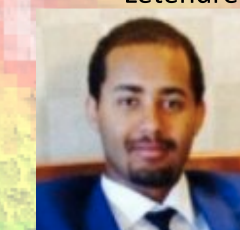
Dr. Matthew Fricke

Dr. Tatiana Paz Flanagan

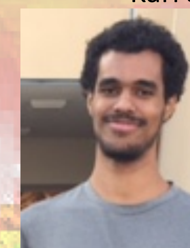
Prof. Judy Cannon



Justyna Tafoya



Kirubel Tadesse



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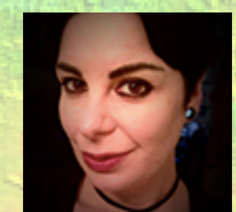
Qi Lu

Manuel Meraz

Jake Nichol

Dr. Paulus Mrass

Janie Byrum



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