



Kinetic modeling of collective behavior: When a good match goes bad







Overview

Overview

Overview

Artificial Successes

Superficial Matches

New Hopes

Conclusions

Artificial Successes

Allocation Kinetics

Superficial Matches

Collective Transport Swarm Assembly

New Hopes

Drift–Diffusion Decision-Making

Conclusions

Collective Transport Decentralized Organization of Teams Carrying Loads



Collective Transport Simplification: Decentralized Boundary Coverage



Stochastic Boundary Coverage Physical Inspiration: Langmuir Adsorption



Stochastic Boundary Coverage Physical Inspiration: Langmuir Adsorption



Overview









 R_0 : free-robot concentration e_U : robot–load-site encounter rate p_B : probability of binding τ_B : mean time before unbinding

Control strategy: Choose probability p_B and time τ_B for desired allocation.







 R_0 : free-robot concentration e_U : robot–load-site encounter rate p_B : probability of binding τ_B : mean time before unbinding

Control strategy: Choose probability p_B and time τ_B for desired allocation. Choices depend on R_0 . Not scalable.







 R_0 : free-robot concentration e_U : robot–load-site encounter rate p_B : probability of binding τ_B : mean time before unbinding

Control strategy: Choose probability p_B and time τ_B for desired allocation. Choices depend on R_0 . Not scalable.

Choices depend on e_U . How to model e_U ab initio?

Stochastic Boundary Coverage Biochemical Inspiration: Catalyzing Enzymes



Stochastic Boundary Coverage Catalyzing Robozymes



- $\frac{[B]}{[U]} = \frac{R_0 e_U p_B}{R_0 e_B p_U} \approx \frac{p_B}{p_U}$
- e_U : robot-load-site encounter rate p_B : probability of binding e_B : robot-bound-complex encounter rate p_U : probability of unbinding

Control strategy: Choose probabilities p_B and p_U for desired allocation.

Stochastic Boundary Coverage Catalyzing Robozymes



$$\frac{[B]}{[U]} = \frac{R_0 e_U p_B}{R_0 e_B p_U} \approx \frac{p_B}{p_U}$$

 R_0 : free-robot concentration e_U : robot–load-site encounter rate p_B : probability of binding e_B : robot–bound-complex encounter rate p_U : probability of unbinding

Control strategy: Choose probabilities p_B and p_U for desired allocation. Scalable.

Stochastic Boundary Coverage Catalyzing Robozymes



- $\frac{[B]}{[U]} = \frac{R_0 e_U p_B}{R_0 e_B p_U} \approx \frac{p_B}{p_U}$
- p_B : probability of binding e_B : robot-bound-complex encounter rate p_U : probability of unbinding

Control strategy: Choose probabilities p_B and p_U for desired allocation. Scalable.

Choices depend on $e_U/e_B = \text{constant} \approx 1$, which has geometric derivation.

Stochastic Boundary Coverage Derivation of Saturation Occupancy



sensu Langmuir

Design case?

Stochastic Boundary Coverage Derivation of Saturation Occupancy



$$\theta_{\max} \stackrel{?!}{=} 0.75$$

Stochastic Boundary Coverage Rényi's Parking Problem Revisited





Stochastic Boundary Coverage Rényi's Parking Problem Revisited



























Collective Transport Decentralized Organization of Teams Carrying Loads





Collective Transport (Wilson et al. 2014)



Collective Transport (Wilson et al. 2014)

Overview
Artificial Successes
Superficial Matches
Collective Transport
Swarm Assembly
New Hopes
Conclusions



Collective Transport (Kumar et al. 2013)



Overview

New Hopes

Conclusions

Collective Transport (Kumar et al. 2013)



Collective Transport (Wilson et al. 2014)



Collective Transport

Decentralized Organization of Ant Teams Carrying Loads



Collective Transport Decentralized Organization of *Ant* Teams Carrying Loads

Overview	_
Artificial Successes	- 3
Superficial Matches	_
Collective Transport	
Swarm Assembly	
New Hopes	

Conclusions





Collective Transport Decentralized Organization of *Ant* Teams Carrying Loads

Overview	•
Artificial Successes	•
Superficial Matches	•
Collective Transport	•
Swarm Assembly	•
New Hopes	•
Conclusions	•





Collective Transport Decentralized Organization of *Ant* Teams Carrying Loads

Overview	•
Artificial Successes	•
Superficial Matches	•
Collective Transport	•
Swarm Assembly	•
New Hopes	•
Conclusions	•




Collective Transport Decentralized Organization of *Ant* Teams Carrying Loads





Possible Extension: Swarm Robotic Assembly (Matthey et al. 2009)



Possible Extension: Swarm Robotic Assembly (Matthey et al. 2009)

Overview	- •
Artificial Successes	•
Superficial Matches	•
Collective Transport	•
Swarm Assembly	•
New Hopes	•
Conclusions	•





Goal: Regulate ratio of assembled parts at equilibrium (e.g., $x_{F1}^* = 2x_{F2}^*$).

Possible Extension: Honeycomb Assembly?

(Seeley and Morse 1976; Pratt 2004; Cargel and Rinderer 2004; Livnat and Pippenger 2006)

Overview

Artificial Successes

- Superficial Matches
- Collective Transport
- Swarm Assembly
- New Hopes
- Conclusions







Later Cell

Earlier Cell

Overview	
Artificial Successes	
Superficial Matches	
Collective Transport	
Swarm Assembly	
New Hopes	Worker + Earlier Cell $\xrightarrow{p_b e_c}$ Worker +
Conclusions	Worker + Later Cell $\xrightarrow{p_u e_c}$ Worker +

Active Cell
$$\xrightarrow{\text{SLOW}}$$
 Finished Cell













Overview
Autificial Currents
Artificial Successes
Superficial Matches
Collective Transport
Swarm Assembly
New Hopes
Conclusions

$$Y p_{YM} - M p_{MY} = 0$$
$$Y p_{YC} - C p_{CY} = 0$$
$$Y + M + C = 1$$





Overview Artificial Successes Superficial Matches Collective Transport Swarm Assembly New Hopes

Conclusions









Overview

Artificial Successes

- Superficial Matches
- Collective Transport
- Swarm Assembly
- New Hopes
- Conclusions











Overview				
Artificial Successes				
Superficial Matches				
New Hopes Drift–Diffusion Decision-Making				
Conclusions		X	×	
	*	×		
•				
•				

Overview				
Artificial Successes				
Superficial Matches				
New Hopes Drift–Diffusion Decision-Making				
Conclusions	Ť.	¥€ ¥€		X

Overview	0 0 0			
Artificial Successes	• • •			
Superficial Matches	0 0 0			
New Hopes Drift–Diffusion Decision-Making				
Conclusions		* * * *		

Overview			
Artificial Successes			
Superficial Matches			
New Hopes Drift–Diffusion Decision-Making Conclusions	A A A A	the contraction of the contracti	
	Slow tran	"Tandem run" sit, but adds one mo	ore recruiter.

Overview	_
Artificial Successes	•
Superficial Matches	• •
New Hopes	•
Drift–Diffusion	•
Decision-Making	•
Conclusions	•
	•
	•
	•





Overview	0 0 0			
Artificial Successes	• • •			
Superficial Matches	0 0 0			
New Hopes Drift–Diffusion Decision-Making				
Conclusions		* * * *		

Overview	
Superficial Matches	
New Hopes Drift–Diffusion Decision-Making	
Conclusions	
	"Transport" Fast transit, but no additional recruiter.

Overview	_
Artificial Successes	•
Superficial Matches	• •
New Hopes	•
Drift–Diffusion	•
Decision-Making	•
Conclusions	•
	•
	•
	•





Overview	-
Artificial Successes	-
Superficial Matches	-
New Hopes	•
Drift–Diffusion	•
Decision-Waking	•
Conclusions	-
	•
	•





Overview				
Artificial Successes				
Superficial Matches				
New Hopes				
Drift–Diffusion Decision-Making				
Conclusions		et al and		
			X	
	X	9		
		When to	switch?	

Recruitment decision process



Recruitment decision process



Recruitment decision process

Role of encounter rate (Pratt 2005)

Role of encounter rate (Pratt 2005)

Role of encounter rate (Pratt 2005)

Encounter-rate detection and estimation? (Ratcliff et al. 1999)

Drift-diffusion model for two-choice tasks (Ratcliff 1978; Ratcliff et al. 1999)

Drift–diffusion model for quorum detection in *Temnothorax*

Overview	•		
Artificial Successes	•		
Superficial Matches	•		
New Hopes	•		lence
Drift–Diffusion Decision-Making	• • •		Evic
Conclusions	•		
	•		
	•		
		Pe	r-ant paramete
	• • • • • •		a: Barrier separat z: Initial evidence T_{nd} : Non-decisio λ_{a} : Critical encou
		Mo	del of conditio
	•		$v \triangleq \lambda - \lambda_c$: Drif
	•		

ers of the model (generalized across sisters):

- ion (response time)
- variable (bias)
- on time (actuation)
- inter rate to detect
- on-dependent confidence/difficulty
 - ft rate (λ measured from encounter data)
Drift–diffusion model for quorum detection in *Temnothorax*

Overview	

Artificial Successes

Superficial Matches

New Hopes

Drift–Diffusion Decision-Making

Conclusions

Best-fit parameter res	ults
------------------------	------

 $\Box \quad a = 26.729$ $\Box \quad z = 8.0$

 $\Box \quad T_{nd} = 6.564 \sec$

 $\ \ \Box \ \ \lambda_c = 0.173 \, {\rm enc/sec}$



Drift-diffusion model for quorum detection in *Temnothorax*

Overview	

Artificial Successes

Superficial Matches

New Hopes

Drift–Diffusion Decision-Making

Conclusions

Best-fit	parameter	results:
----------	-----------	----------

 $\Box \quad a = 26.729$

- $\Box \quad z = 8.0$
- $\Box \quad T_{nd} = 6.564 \sec$
- $\hfill\square$ $\lambda_c=0.173\, {\rm enc/sec}$

Drift-diffusion model for quorum detection in *Temnothorax*



Random walk: internal or external?

Overview	
Artificial Successes	
Superficial Matches	
New Hopes	
Drift–Diffusion	
Decision-Making	
Conclusions	
	Enden

Random walk: internal or external?





Recurrence time distributions?

Conclusions

Overview
Artificial Successes
Superficial Matches
New Hopes

Conclusions

Coarse-graining introduces ambiguity

Macroscopic consistencies can come about through multiple mechanisms

Conclusions

Overview
Artificial Successes
Superficial Matches
New Hopes

Conclusions

- Coarse-graining introduces ambiguity
- Macroscopic consistencies can come about through multiple mechanisms
- Simplest mechanisms are great candidates for engineering design
- Nature's adaptive mechanisms are constrained by phylogeny, ontogeny, and the environment (Tinbergen!)

Conclusions

Overview
Artificial Successes
Superficial Matches
New Hopes

Conclusions

- Coarse-graining introduces ambiguity
- Macroscopic consistencies can come about through multiple mechanisms
- Simplest mechanisms are great candidates for engineering design
- Nature's adaptive mechanisms are constrained by phylogeny, ontogeny, and the environment (Tinbergen!)

Acknowledgments:

- □ Spring M. Berman (ASU, SEMTE) + laboratory
- □ Stephen C. Pratt (ASU, SOLS) + laboratory