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On Biologically-Inspired Control Methods in Modern Communication Networks

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Introduction

- Why use methods from biology?
  - Certain network types are desired to operate in a distributed/cooperative manner (sensor networks, P2P, Ad-Hoc) without central control
- New protocols/architectures are required:
  - scalable to the size of the network
  - robust to failures of nodes and links
  - adaptive to changes in network conditions
  - fully distributed and self-organizing

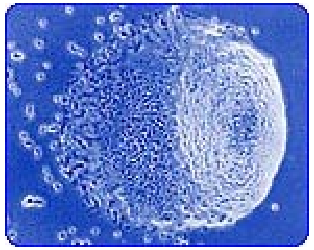
➔These features are often found in biology

Biologically-Inspired Mechanisms

- The emergent collective intelligence of groups of simple agents (**swarm intelligence**).
  - Ant trail (foraging behavior of ants)
  - Cemetery organization and brood sorting
  - Colonial closure
  - Division of labor and task allocation
  - Pattern forming
  - Synchronization in flashing fireflies

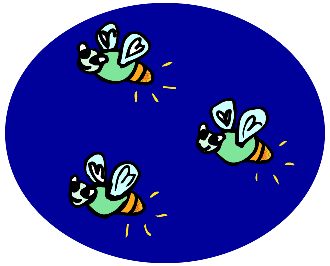
- A group exhibits an intelligent and organized behavior without any centralized control, but with local and mutual interactions among individuals (**stigmergy**)
- The behavior is adaptive to changes in the environment
- A group keeps working even if a part fails

Bio-inspired Examples



Overlay Network Symbiosis

symbiosis of different cells, organisms, groups, and species



Waveform Synchronized Data Gathering

synchronized flashes in a group of fireflies

Reaction-Diffusion based Control Scheme for Sensor Networks

pattern formation on the surface of the body of an emperor angelfish

Scalable Ant-based Routing Scheme

foraging behavior of ants

Self-Organization

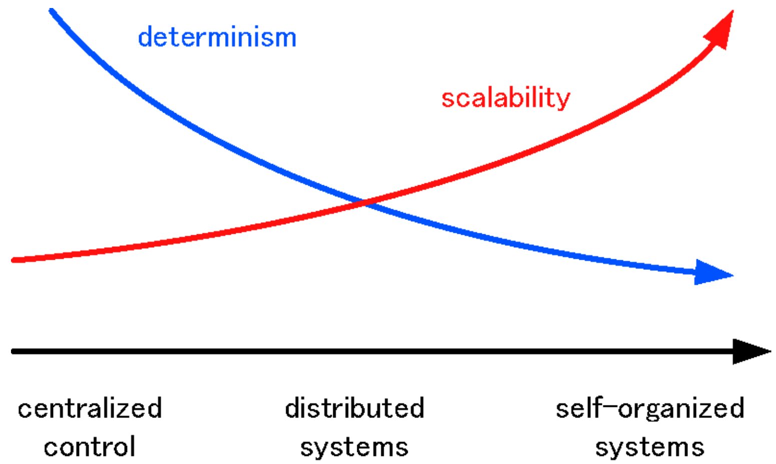
Self-organization is a set of ***dynamical*** *mechanisms whereby structures appear at the global level of a system from* ***interactions among its lower-level components****. The rules specifying the interactions among the system's constituent units are executed on the basis of purely logical information, without reference to the global pattern which is an* ***emergent*** *property of the system rather than a property imposed upon the system by an external ordering influence.*

E. Bonabeau, M. Dorigo, G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*, Oxford University Press, 1999.

Self-Organization (2)

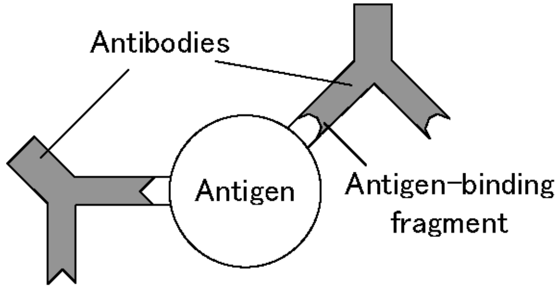
- Four principle mechanisms for self-organization in biological systems:
  - **positive feedback** permits evolution and promotes creation of structure (reinforcement)
  - **negative feedback** regulates influences from previous bad adaptations (saturation, competition)
  - **direct** or **indirect interaction** among individuals
  - utilization of inherent **randomness** and **fluctuations**

- **However ...**
  - Scalability of system comes at the cost of determinism
  - Adaptation speed is rather slow (**evolution**)



Biologically-Inspired Networks

- Using analogies of cell/tissue/organ hierarchy for autonomous networking
- Artificial immune systems for reaction to intruding cells (**network security**)



- Bio-Networking Architecture provides architecture and middleware based on cooperation and evolution of individuals.
  J. Suzuki and T. Suda, *A middleware platform for a biologically inspired network architecture supporting autonomous and adaptive applications*, IEEE Journal on Selected Areas in Communications, 23(2), 249-260, 2005.

Case Study 1

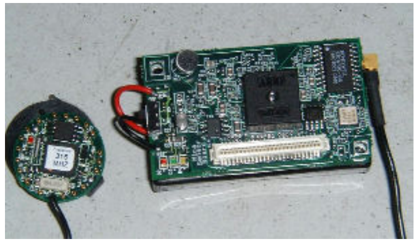
Waveform Synchronized Data Gathering in Sensor Networks

based on synchronized flashing in a group of fireflies

N. Wakamiya and M. Murata, *Synchronization-based Data Gathering Scheme for Sensor Networks*, IEICE Transactions on Communications (Special Issue on Ubiquitous Networks), Vol. E88-B, No. 3, pp. 873-881, March 2005.

Sensor Networks

- Sensor nodes are equipped with sensor (heat, temperature), wireless transmitter, battery unit



MOTE2
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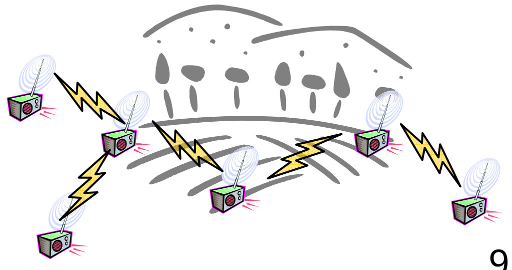
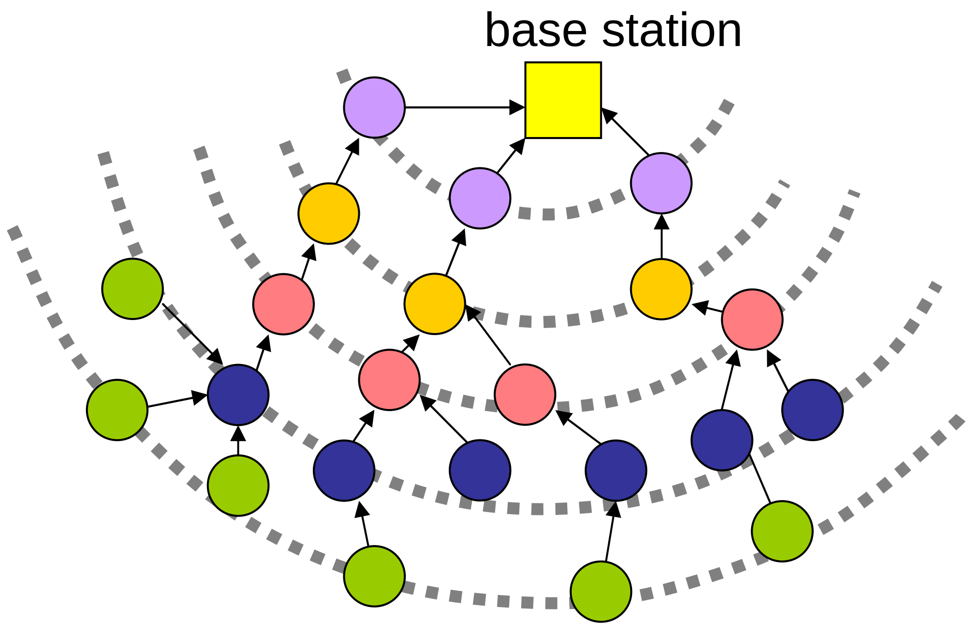
- Applications：
  - Health and welfare (vital signs, safety)
  - Crime prevention and security
  - Disaster prevention (fire, landslide, flood, earthquake)
  - Environment (weather, water/air pollution)

- Requirements:
  - large number of nodes required
  - deployed in an uncontrolled and unorganized way
  - may halt due to depletion of the battery or failure



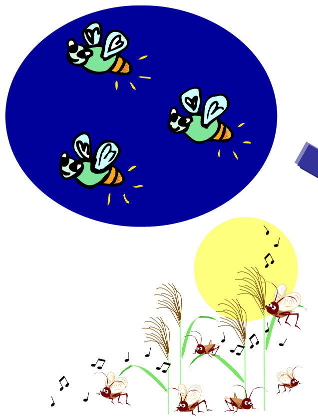
Periodic Data Gathering

- Collect sensor information from all sensor nodes at regular intervals
- Save energy consumption by multi-hop communication
  - sensor information propagates from the edge to the base station
- Each node receives information from more distant nodes, aggregates it with its own information, and sends it to the next node
- Information is propagated in concentric circles



Synchronized Data Gathering

- A group of fireflies flashes synchronously
- Each firefly decides its timing of flashing by observing its surroundings (flashing of neighboring fireflies)
  ➔ **fully-distributed and self-organizing**
- By adopting the mechanism, sensor nodes come to synchronization without any centralized control



pulse-coupled oscillator model

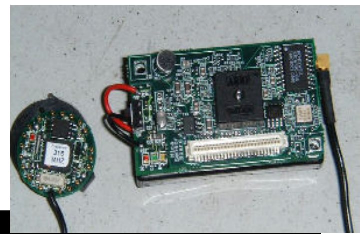
a set of oscillators $\mathbf{O} = \{O_1, \cdots, O_N\}$

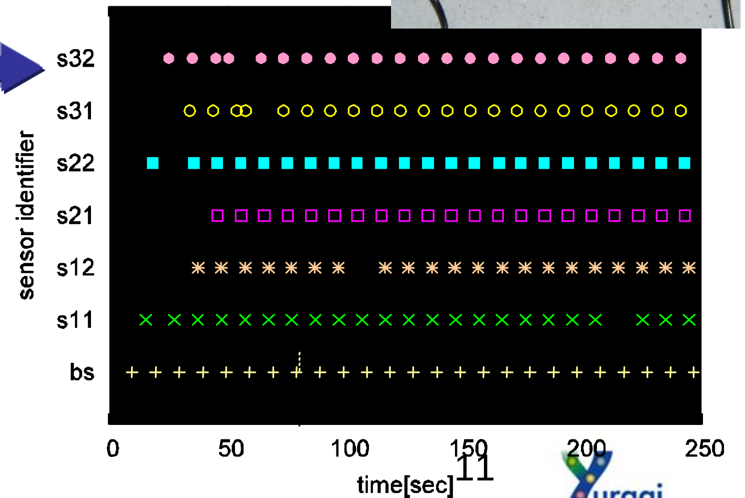
phase-state function

$$x_i = f_i(\phi_i),\quad f_i : [0,1] \to [0,1],\quad i = 1, \cdots, N$$
$$= \frac{1}{b} \ln\left[1 + \left(e^b - 1\right)\phi_i\right]$$

stimulation

$$x_i(t) = 1 \Rightarrow x_j(t^+) = \min\left(1, x_j(t) + \varepsilon_i(\phi_j)\right)$$





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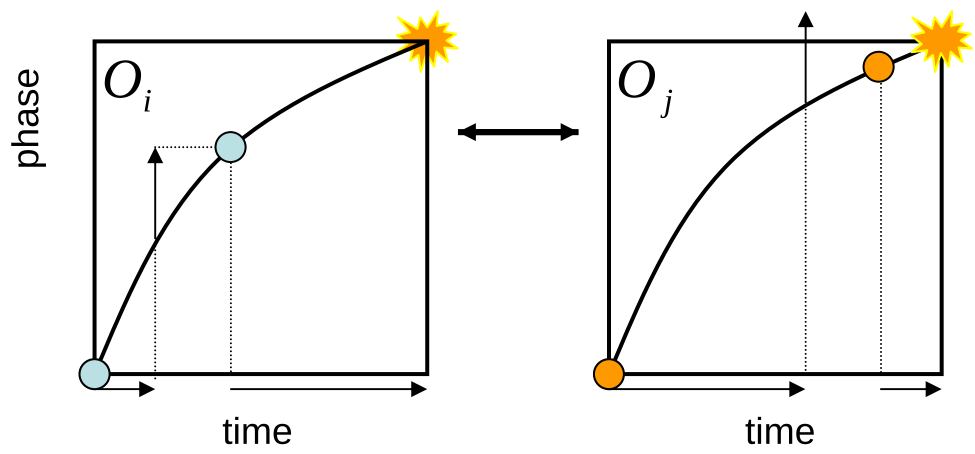
Pulse-Coupled Oscillator Model

- A set of oscillators $\mathbf{O} = \{O_1, ..., O_N\}$
- Oscillator O_i has phase $\phi_i \in [0,1]$ and state $x_i \in [0,1]$
  $$x_i = f_i(\phi_i) \text{ with } f_i : [0,1] \rightarrow [0,1] \text{ and } i = 1, ..., N$$
- When state x_i reaches 1, the oscillator fires
- A coupled oscillator O_j is stimulated and raises its state
- When oscillator O_j also fires from stimulus, both are synchronized



Conclusion for Case Study 1

The proposed method can collect sensor information from a large number of randomly distributed sensors at regular intervals in an energy-efficient way

- simple and easy to implement
- fully-distributed and self-organizing
- longer lifetime of a sensor network
- no initial setting of sensor nodes and no careful planning
- adapts to addition, removal, and movement of sensor nodes
- adapts to changes in frequency of data gathering

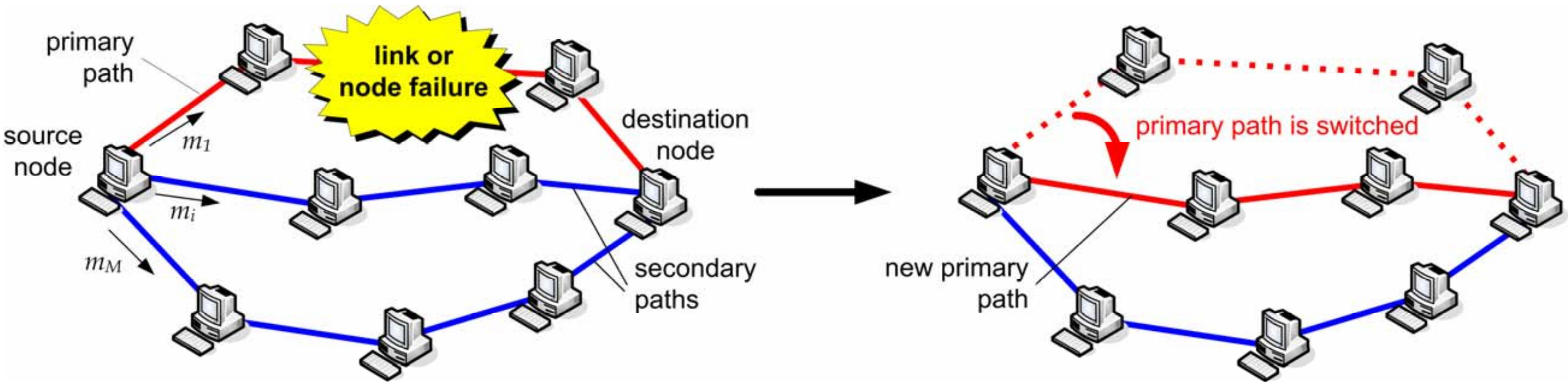
Case Study 2

Multi-Path Routing in Overlay Networks with Attractor Selection

based on the adaptive response in E. Coli cells
to the availability of a nutrient

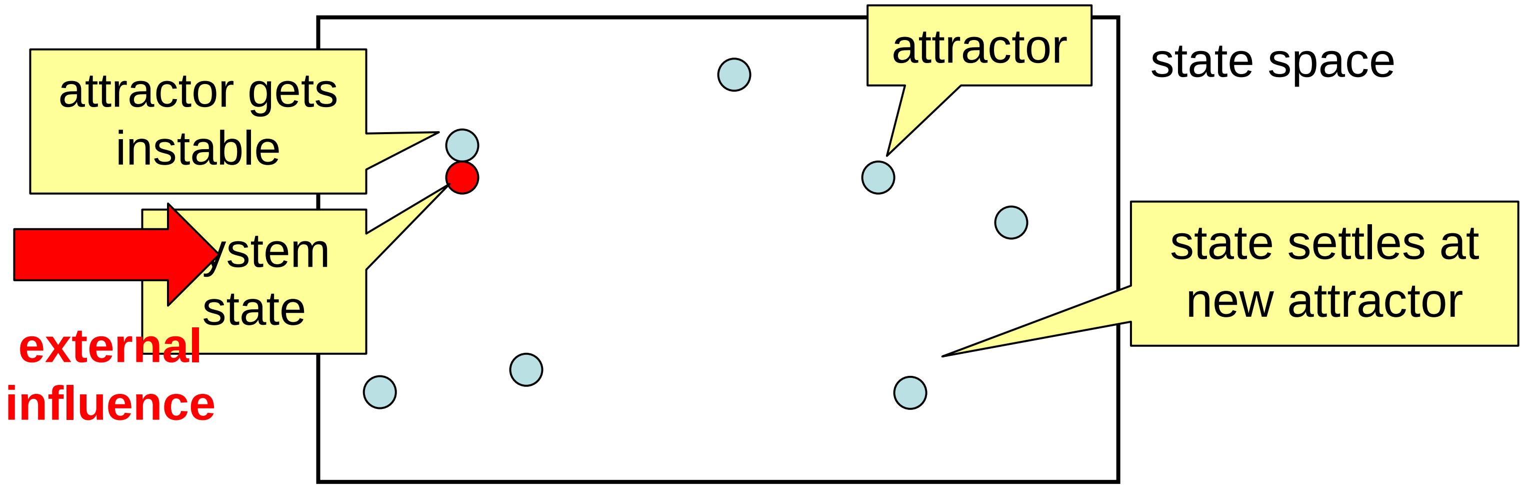
K. Leibnitz, N. Wakamiya, and M. Murata, *Biologically-Inspired Self-Adaptive Multi-Path Routing in Overlay Networks*, Communications of the ACM, Vol. 49, No. 3, pp. 62-67, March 2006.

Our Objective



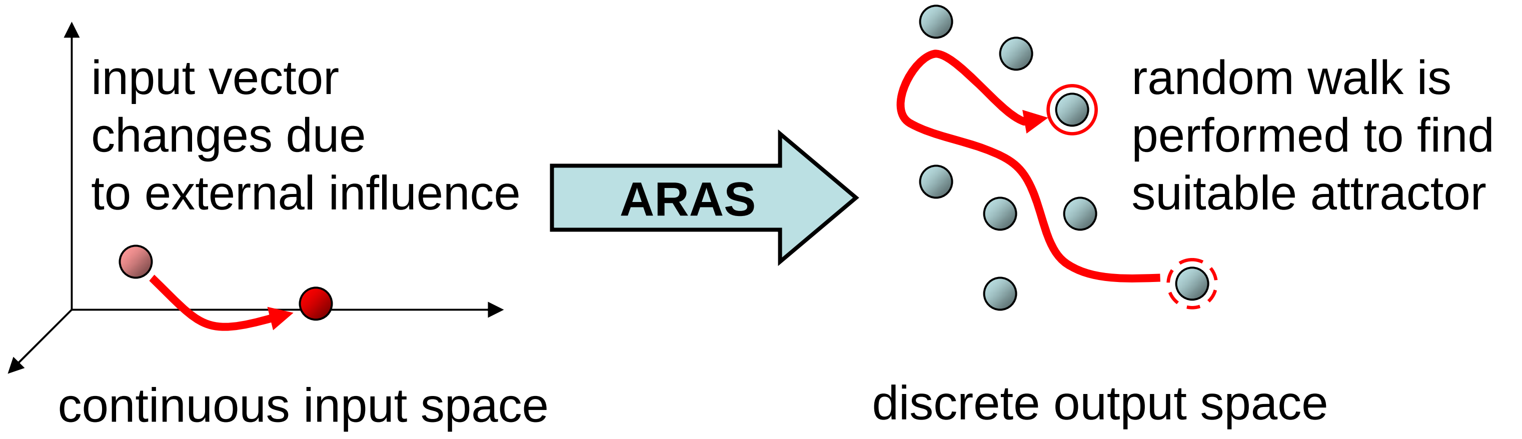
- Select paths in a multi-path overlay network environment
- Apply randomization in path selection to reduce selfishness
- Consideration of *primary* and *secondary* paths with transmission rates m_i
- Inline measurements of path metrics (e.g. RTT)
- Original model for E. coli cells to adapt to changes in the availability of a nutrient

Adaptive Response by Attractor Selection



- Basic mechanism:
  - consider state space with magnets (attractors)
  - solution is a metal ball which is constantly in motion but stays locked at an attractor
  - activity influences which magnet is activated and the strength of the noise influence

Summary of ARAS Principle



- ARAS can be seen as a mapping of an input space (environment) to a set of discrete points (attractors)
- When a solution is not suitable, the activity value causes a random walk towards a better solution.

Mathematical Model

target value also influenced by other m_i

if activity α is 0 only noise term remains

zero-mean Gaussian noise term

$$\frac{dm_i}{dt} = \frac{syn(\alpha)}{1 + m_{\max}^2 - m_i^2} - deg(\alpha)\, m_i + \eta_i$$

- Formulation as differential equations with mutual influence
- Attractor locations are entirely defined by the differential equations themselves
- Activity α makes the first two terms become zero
  ➔ system behaves like a random walk

$$\frac{d\alpha}{dt} = \delta \left(\prod_{i=1}^{M} \left[\left(\frac{m_i}{m_{\max}} \frac{l_{\min}}{l_i + \Delta} \right)^n + 1 \right] - \alpha \right)$$

target values are influenced by current state and input

l_i are input values and Δ is a hysteresis threshold

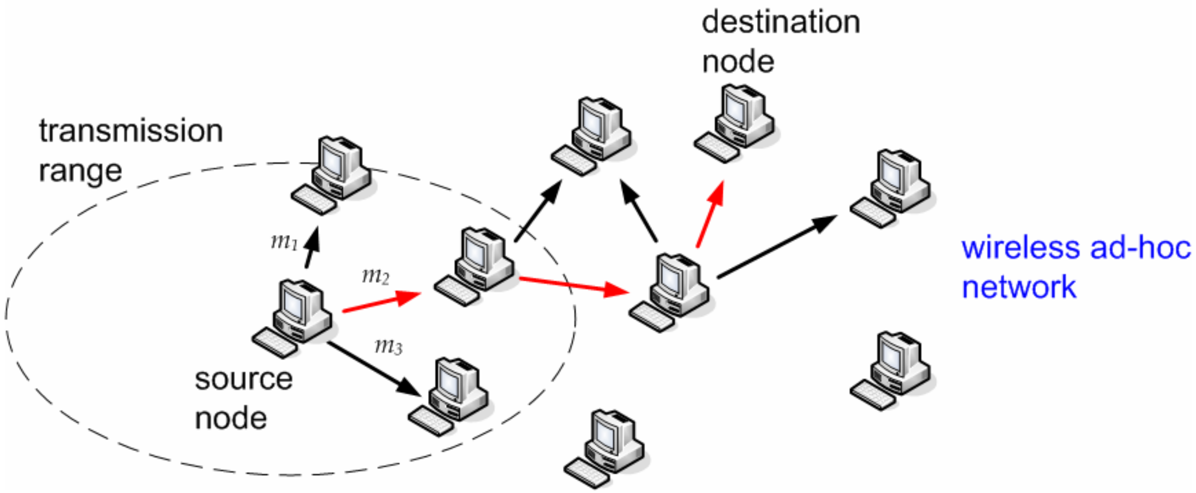
Application to Multi-Path Routing

- Route Setup Phase
  - Find disjoint paths from source to destination
  - Paths are found by broadcasting probe packets
- Route Maintenance Phase
  - Use ARAS to select best path
  - Randomization in path selection (primary & secondary paths)
  - Hysteresis threshold to avoid path flapping
  - Input metric taken from measurements (e.g. RTT, available bandwidth)

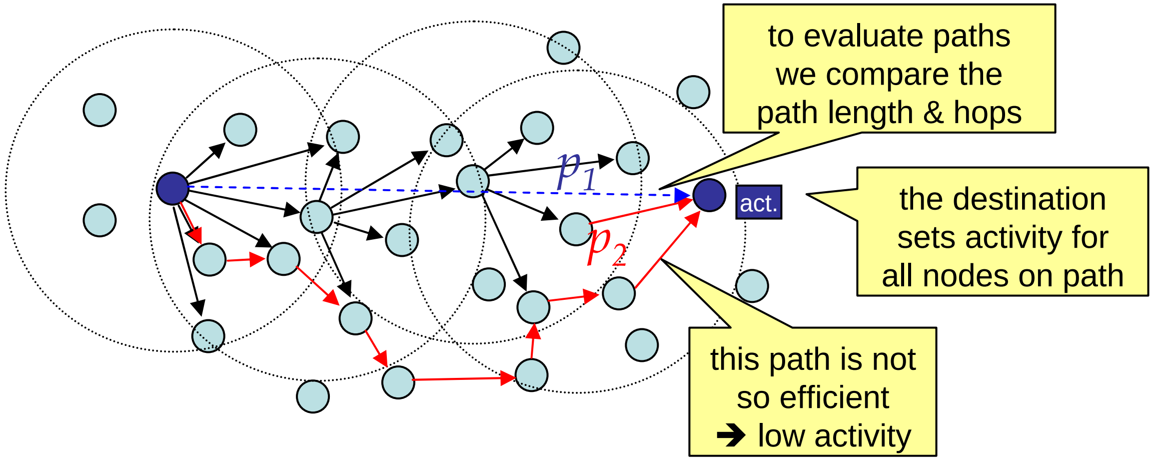
randomization & hysteresis for reducing selfishness

Extension to Hop-by-Hop Behavior

- So far we only considered the selection among a set of predefined candidates.
  ➔ next step is finding the candidates
- Scenario is ad-hoc network
- Each node can transmit to any neighbor

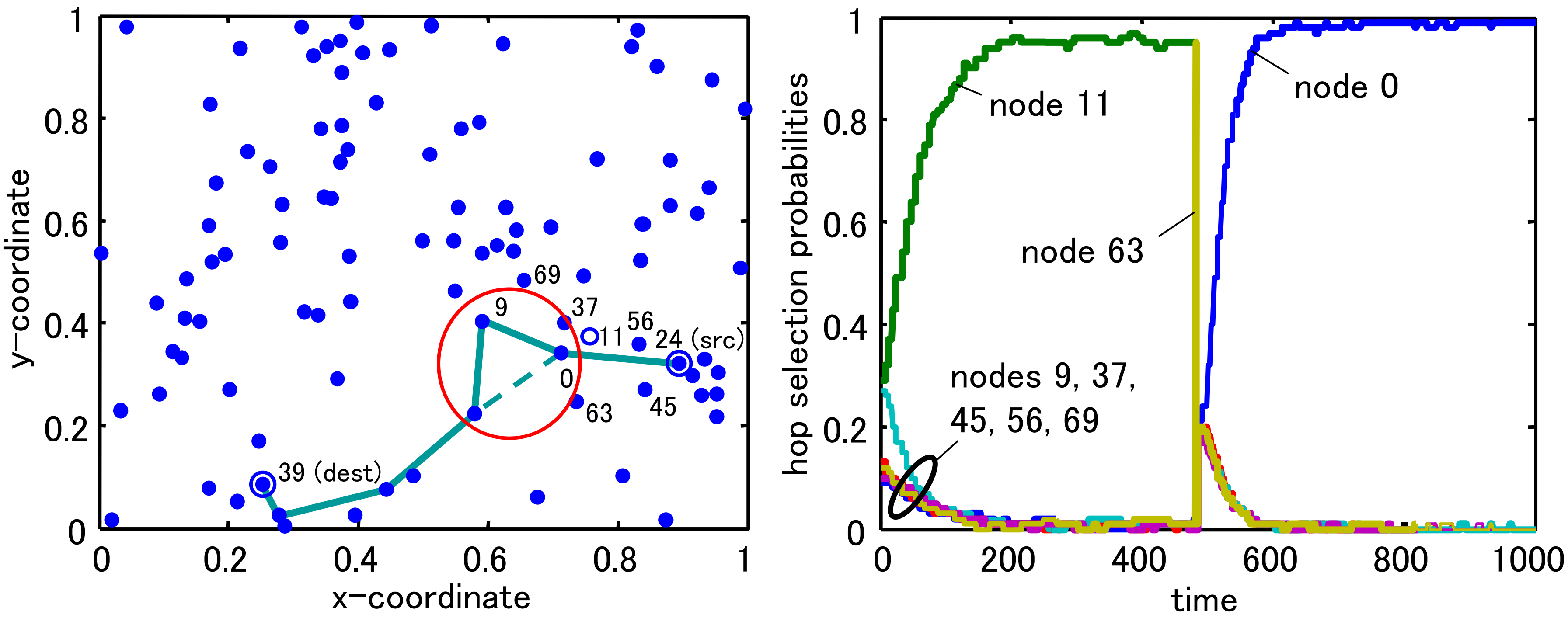


ARAS in Ad-Hoc Scenario



- Next-hop candidate nodes are maintained in sets
- Packets are forwarded to the primary node selected by ARAS
- Efficiency of path (path length/hop count) is propagated through activity to all nodes along path
  ➔ similar to reinforcement learning

Example Behavior



- Right are the hop selection probabilities of node 24: First, node 11 is chosen as next hop, but after $t = 500$ is switched to node 0

Conclusion for Case Study 2

The proposed method can choose the best path in a self-adaptive and efficient way and can be tuned to reduce the selfish behavior of routing

- Path selection scheme in overlay networks and next hop selection in ad-hoc networks based on biological attractor selection model
- Parameters of the model are chosen such that selfishness is reduced
- Interactions of flows leads to symbiotic solutions
- Future work:
  - Large scale network experiments
  - Investigation of different input metrics or their combinations

Perspective and Caveats

- By getting inspiration from biological systems, we can establish fully-distributed and self-organizing technologies.
- However, we have to consider,
  - the rate of adaptation is rather slow
  - they do not necessarily provide the best performance

We should refrain from simply mimicking biology!

But instead we should:

1. Build a mathematical model
2. Carefully consider which part of the model leads to the desirable feature of the biological system
3. Move to the application of the model and establish a more concrete mechanism