

A Bio-Inspired Robust Routing Protocol for Mobile Ad Hoc Networks

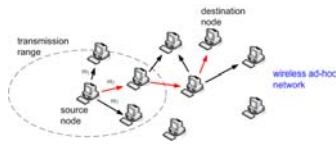
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Outline of Presentation

- Introduction and motivation
- Adaptive response by attractor-selection
- Application to routing in MANET
- Simple numerical examples
- Conclusion and outlook

Introduction



- Required features in ad-hoc network routing: scalable, robust, adaptive, fully distributed, and self-organizing
 - Can often be found in biological systems (e.g. *swarm intelligence*)
- **Main idea:** randomized, noise-driven selection of next hop using bio-inspired method

Adaptive Response by Attractor-Selection (ARAS)

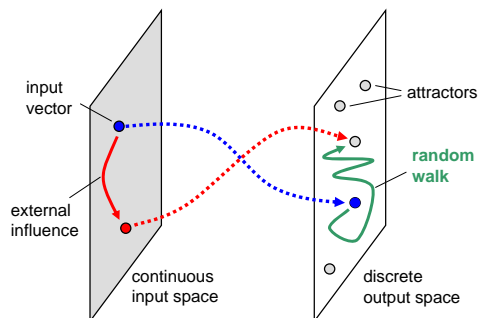
- Method from cell biology:
 - reaction to lack of nutrient when no signaling pathway exists from environment to DNA
 - **attractor:** region within which the orbit of dynamical system returns regardless of initial conditions and noise
 - **activity:** mapping of environment to “goodness” of current system state
- Description by Langevin-type of stochastic differential equation system

$$\frac{dm_i}{dt} = f(m_1, \dots, m_M) \times \alpha + \eta_i$$

noise

activity

General Concept of ARAS



Mathematical Model of ARAS

- Consider a system with M possible choices given by vector $\mathbf{m} = [m_1, \dots, m_M]$

$$\frac{d\mathbf{m}}{dt} = \frac{s(\alpha)}{1 + \max(\mathbf{m})^2 - \mathbf{m}^2} - d(\alpha) \mathbf{m} + \boldsymbol{\eta}$$

- The factors $s(\alpha)$ and $d(\alpha)$ are the rate of *synthesis* and *degradation* and are functions of the activity α

$$s(\alpha) = \alpha[\beta \alpha^\gamma + \varphi^*]$$

$$d(\alpha) = \alpha$$

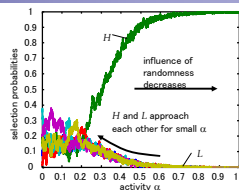
- $\boldsymbol{\eta} = [\eta_1, \dots, \eta_M]$ is vector with white noise

Mathematical Model (2)

- Define $\varphi(\alpha) = \frac{s(\alpha)}{d(\alpha)}$
- In equilibrium there are M solutions with entries:

$$\bar{m}_i^{(k)} = \begin{cases} \varphi(\alpha) & i = k \quad H \text{ value} \\ \frac{1}{2} \left[\sqrt{4 + \varphi(\alpha)^2} - \varphi(\alpha) \right] & i \neq k \quad L \text{ value} \end{cases}$$

- Both values H and L merge at $\varphi^* = \frac{1}{\sqrt{2}}$



Activity Dynamics

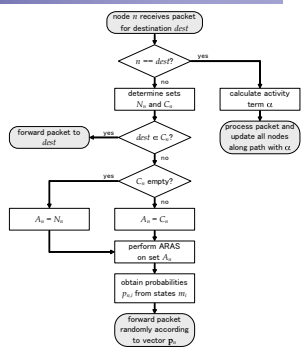
- Activity α reflects the “goodness” of the system

$$\frac{dm_i}{dt} = f(m_1, \dots, m_M) \times \alpha + \eta$$

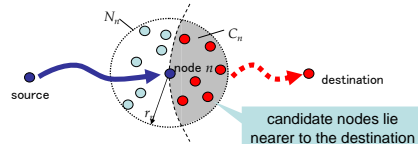
- Basic behavior:
 - $\alpha \approx 0$: dynamics dominated by noise term
 - $\alpha \approx 1$: convergence to attractor (noise influence recedes)
- We use *packet delivery ratio* of a flow as activity

MANET Routing with ARAS

- Consider reactive routing like AODV
- RREQ (*route requests*) are flooded for new/broken paths
- Each node maintains *next hop probability vector p* which is initialized by RREP
- Route maintenance uses neighbor and candidate sets



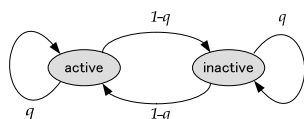
Route Maintenance Phase



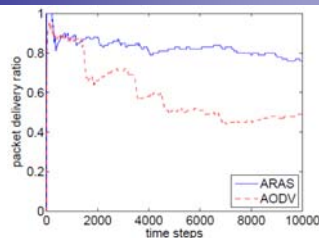
- At certain intervals, all nodes are probed for their relative distance to the destination and stored in sets: *neighbor set N_n*, *candidate set C_n*
- Next hop is chosen randomly according to probability vector p
- ARAS state values m_i decay over time at rate δ

Numerical Evaluation

- Nodes randomly distributed in unit square with spatial homogeneous Poisson process of density λ
- Transmission range $r = 0.2$
- Duration of each simulation $T_{max} = 10000$, each simulation repeated 1000 times
- Node activity model with transition probability q

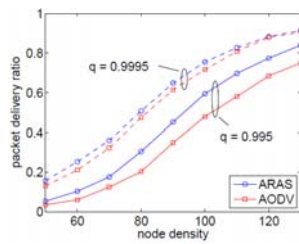


Sample Trace Run



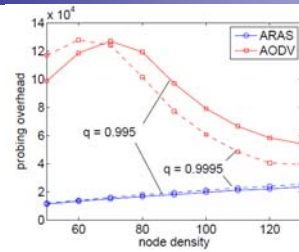
- Parameters: $\lambda = 120$, $q = 0.995$, $r = 0.2$
- Identical simulation conditions and layout
- AODV degrades over time, ARAS remains constant

Packet Delivery Ratio



- When q is high, both methods are nearly equal
- Packet delivery is improved over AODV when there are frequent changes in activity phases

Probe Packet Overhead



- Density has only small influence on proposal
- AODV overhead decreases with density, as path is found quicker (not all probe packets considered here)

Conclusion and Outlook

- Biologically-inspired method for selecting next hop in ad-hoc networks
- Increased resilience through stochastic routing
- Feedback-based (reinforcement learning)
- Future work:
 - More comparisons with other routing methods
 - Investigation of other possibilities for activity mappings
 - Prototype implementation