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

Kenji Leibnitz, Naoki Wakamiya, Masayuki Murata
Osaka University
{leibnitz, wakamiya, murata}@ist.osaka-u.ac.jp

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

Mathematical Model of ARAS

• Consider a system with \( M \) possible choices given by vector \( \mathbf{m} = [m_1, \ldots, m_M] \)

\[
\frac{dm}{dt} = \frac{s(\alpha)}{1 + \max(m)} - d(\alpha) m + \eta
\]

• The factors \( s(\alpha) \) and \( d(\alpha) \) are the rate of synthesis and degradation and are functions of the activity \( \alpha \)

\[
s(\alpha) = a [b \alpha^2 + \psi^+] \\
d(\alpha) = \alpha
\]

• \( \eta = [\eta_1, \ldots, \eta_M] \) is vector with white noise

General Concept of ARAS
Mathematical Model (2)

- Define $\phi(\alpha) = \frac{e^{\alpha}}{1 + e^{\alpha}}$
- In equilibrium there are $M$ solutions with entries:
  
  \[
  m_i^{(h)} = \begin{cases} 
  \phi(\alpha) & i = k \text{ H value} \\
  \frac{1}{2}\left(4 + \phi(\alpha)^2 - \phi(\alpha)\right) & i \neq k \text{ L value}
  \end{cases}
  \]
- Both values $H$ and $L$ merge at $\phi^* = \frac{1}{\sqrt{2}}$

Activity Dynamics

- Activity $\alpha$ reflects the "goodness" of the system
  
  \[
  \frac{dm_i}{dt} = \left(\prod_{j \neq i}^N m_j\right) \times (1 + m_i^{(l)})
  \]
- Basic behavior:
  - $\alpha = 0$: dynamics dominated by noise term
  - $\alpha = 1$: 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 $\delta$

Numerical Evaluation

- Nodes randomly distributed in unit square with spatial homogeneous Poisson process of density $\lambda$.
- Transmission range $r = 0.2$
- Duration of each simulation $T_{\text{max}} = 10000$, 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