Analysis of Interaction between Layered Self-organizing Network Control

Naoki Wakamiya and Masayuki Murata

Graduate School of Information Science and Technology, Osaka University
1-5 Yamadaoka, Suita, Osaka 565-0871, Japan
Email: {wakamiya,murata}@ist.osaka-u.ac.jp

Abstract—Self-organization is considered one of key design principles to build highly scalable, adaptive, and robust new generation networks. As such, there have been several attempts to establish self-organization based network architecture and control in these years. However, it is not clear how multiple self-organizing mechanisms interact with each other once they are combined together. In this paper, we analyze interaction between layered control mechanisms for autonomous and adaptive routing in a wireless ad-hoc network, which adopt a nonlinear mathematical model called the attractor selection model. The degree of coupling corresponds to the way that two mechanisms share parameters. Through simulation experiments, we investigate the relationship between the degree of coupling and the performance of layered self-organizing control mechanisms.

1. Introduction

A new generation network is required to accommodate and handle a tremendous number of nodes and an enormous amount of traffic, which have the highly heterogeneous and dynamic nature. The conventional design methodology is not feasible any more, which optimizes the network system assuming given and predicted operational conditions to achieve the best performance. Furthermore, centralized control is not possible for the extra overhead to maintain the up-to-date information about the whole network system. Self-organization is considered one of key design principles to build highly scalable, adaptive, and robust new generation networks. In self-organized systems, each entity decides its behavior based on a set of simple rules and the local observation. Through mutual direct and/or indirect interaction among entities, the globally organized pattern eventually emerges.

To realize self-organizing control mechanisms for a new generation network, we take an approach to adopt biologically-inspired mathematical models [1]. Biological systems are self-organizing. They are scalable, adaptive, and robust. For example, *E. coli* cells autonomously select nutrients to synthesize in order to live and grow in the dynamically changing nutrient condition of the environment [2]. They do not have a signal transduction network to trigger synthesis of an appropriate nutrient according to environmental nutrient condition. Instead, adaptive selection of nutrient synthesis is driven by noise or fluctuation.

The attractor selection model, whose brief introduction will be explained in the next section, is a nonlinear mathematical model imitating the adaptive behavior of bacteria. For its high adaptation capability, the attractor selection model has been applied to overlay multipath routing and mobile ad-hoc network routing. Simulation and experimental results demonstrate that the attractor selection-based control is adaptive to topology changes caused by mobility and robust to failures. Regarding other self-organizing control mechanisms adopting biological models, such as ACO (Ant Colony Optimization), a response threshold model of division of labors, and a reaction-diffusion model of autonomous pattern formation, they are shown to be scalable, adaptive, and robust. However, it is not clear what would happen when two or more self-organizing control mechanisms are incorporated with each other.

In this paper, taking attractor selection-based mechanisms as examples of self-organizing control, we investigate the relationship between the degree of interdependency or coupling and the performance of layered self-organizing control, more specifically, overlay routing and mobile ad-hoc network routing.

2. Attractor Selection Model

The attractor selection model is formulated in the form of a Langevin type of equation.

$$\frac{d\vec{x}}{dt} = \vec{f}(\vec{x}) \cdot \alpha + \vec{\eta} \tag{1}$$

$\vec{x}$ corresponds to the state of a system. In the case of *E. coli* cells, $\vec{x}$ stands for the mRNA concentrations, which control nutrient synthesis. Function $\vec{f}$ defines attractors of a dynamic system, where the state of a dynamic system stably stays after the transition phase. Attractors corresponds to alternatives of control or behavior, such as nutrient synthesis. α is called *activity*, which means the goodness of control or behavior, e.g. the cellular growth rate. Finally, $\vec{\eta}$ expresses internal and external noise.

In the case of an attractor selection-based routing mechanism, attractors correspond to next-hop nodes to forward a packet. $\vec{x}$ is defined for next-hop nodes where $||\vec{x}||$ is equal to the number of neighbor nodes. When the current packet forwarding is not appropriate, the activity becomes small.

Then, the term $\vec{f}(\vec{x}) \cdot \alpha$ becomes small. Consequently, the relative influence of the noise term $\vec{\eta}$ becomes dominant. The node looks for new appropriate next-hop node, i.e. a good attractor, by being driven by random and stochastic selection. Eventually the node finds and reaches a new good attractor. The performance improves, the activity increases, and the force of entrainment of a new attractor becomes strong. Finally, the state of the node becomes stable. In this way, an intermediate node adaptively chooses a next-hop node which leads to the better performance, that is, a larger activity α.

3. Layered Self-Organizing Control

As self-organizing control, we consider attractor selection-based routing mechanisms, whose details can be found in [3]. A node, which contributes to both of overlay routing and MANET routing, have two state vectors, $\vec{x}_O$ and $\vec{x}_M$ for overlay and MANET, respectively. When overlay and MANET routing is independent, attractor selection equations become,

$$\frac{d\vec{x}_O}{dt} = \vec{f}(\vec{x}_O) \cdot \alpha_O + \vec{\eta}_O \tag{2}$$

$$\frac{d\vec{x}_M}{dt} = \vec{g}(\vec{x}_M) \cdot \alpha_M + \vec{\eta}_M \tag{3}$$

In this independent layered control, terms α_O and α_M mean that each of routing mechanisms has their own goals or performance measures, such as the end-to-end delay, the number of hops, and the packet delivery ratio.

Following the attractor selection model, there are alternatives of coupling.

- MANET-aware overlay routing: An overlay network chooses a overlay path which improves the performance of MANET routing, for example, by detouring a congested area.

$$\frac{d\vec{x}_O}{dt} = \vec{f}(\vec{x}_O) \cdot \alpha_O \cdot \alpha_M + \vec{\eta}_O \tag{4}$$

$$\frac{d\vec{x}_M}{dt} = \vec{g}(\vec{x}_M) \cdot \alpha_M + \vec{\eta}_M \tag{5}$$

- Overlay-aware MANET routing: A MANET chooses a physical path connecting two overlay nodes, which leads to better overlay end-to-end performance.

$$\frac{d\vec{x}_O}{dt} = \vec{f}(\vec{x}_O) \cdot \alpha_O + \vec{\eta}_O \tag{6}$$

$$\frac{d\vec{x}_M}{dt} = \vec{g}(\vec{x}_M) \cdot \alpha_M \cdot \alpha_O + \vec{\eta}_M \tag{7}$$

- Tight coupling: Both of overlay and MANET try to maximize the total performance by sharing the same goal. $\alpha_O \cdot \alpha_M$ can be replaced with a single activity α.

$$\frac{d\vec{x}_O}{dt} = \vec{f}(\vec{x}_O) \cdot \alpha_O \cdot \alpha_M + \vec{\eta}_O \tag{8}$$

$$\frac{d\vec{x}_M}{dt} = \vec{g}(\vec{x}_M) \cdot \alpha_M \cdot \alpha_O + \vec{\eta}_M \tag{9}$$

Intuitively speaking, the tight coupling leads to the best performance among the above four alternatives including the independent case. However, the global optimization with multiple criteria is harder to achieve and it would take longer time than the other couplings. Furthermore, the tight control is vulnerable to failures and unexpected events. Going back to biological systems, they are not fully optimized, incomplete, and redundant. However, such non-optimality, incompleteness, and redundancy are the source of adaptability and robustness.

In the final version of paper, we show results of evaluation to investigate the relationship among the degree of coupling and performance of layered self-organizing mechanisms.

References

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