IEICE Proceeding Series

Analysis of Coupling Effect of Layered Network Control

Naoki Wakamiya, Masayuki Murata

Vol. 1 pp. 727-730
Publication Date: 2014/03/17
Online ISSN: 2188-5079

2012 International Symposium on Nonlinear Theory and its Applications
NOLTA2012, Palma, Majorca, Spain, October 22-26, 2012

Analysis of Coupling Effect of Layered 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—An information network has hierarchical structures both physically and functionally. Higher-layer control is always influenced by lower-layer behavior and lower-layer control always behaves in accordance with requests issued by higher-layer control. Although there are lessons learned from practical experiments, simulation experiments, and mathematical analysis, interactions between layered network control methods is not fully explored. In this paper, we analyze interaction between layered control mechanisms, more specifically, adaptive routing protocols based on a nonlinear mathematical model. We change the degree of coupling of two layers and evaluate the convergence time and the path length. Results show that lower-layer routing with higher-layer awareness provides the better performance, which suggests similarity to perception process of ambiguous figures in the human brain.

1. Introduction

An information network has hierarchical structures both physically and functionally. Based on the OSI reference model [1], seven layers are defined, i.e. application, presentation, session, transport, network, data link, and physical from the top to the bottom. One of the main purposes of the layered architecture is modularity of networking functions. Each layer provides a higher layer with certain networking functions through the layer boundary while hiding details of structures, mechanisms, and states of lower layers. For example, the network layer is responsible for relaying packets toward the destination node, i.e. routing. The transport layer, which lies above the network layer, can ensure that all segments arrive at the destination node by using the routing function of the network layer. Because of the modularity, any protocol can be introduced to a network, as far as it offers the appropriate services to upper-layer protocols by using services provided by lower-layer protocols through inter-layer interfaces.

In the original reference model layers were designed so that information flow across layer boundaries was minimized. However, researchers have been considering a cross-layer architecture which allows stronger interactions and interdependency between layers or even incorporating different layers into one [2]. Especially for a wireless sensor network, cross-layer control is preferred, because the architecture with many layers is too complicated and resource expensive for a tiny device with the small amount of memory and the poor processing capacity [3]. Furthermore, by using internal information of other layer, the optimality of control can be expected to increase, e.g. path selection considering the radio quality.

Regarding the physical hierarchy, it is well known that the Internet is a collection of networks, called AS (Autonomous System) which is managed by a certain routing policy. An AS corresponds to a network of an ISP (Internet Service Provider), for example, and it consists of a large number of routers, physical links, and other networking facilities. ASs are connected with each other to have the global connectivity. The BGP (Border Gateway Protocol) is used for inter-AS routing and IGPs (Interior Gateway Protocols) such as RIP and OSPF are used for intra-AS routing. Therefore, from a viewpoint of BGP, a network consists of ASs and their internal structures are hidden. Then, we can regard an AS-level topology as a higher-layer structure and router-level topologies as lower-layer structures. In the context of overlay networking, a logical network, which consists of hosts exchanging messages and virtual links representing sessions and connections established between hosts, is built over physical networks. Furthermore, with the rapid development of network virtualization technologies, we can build multiple virtual networks over physical networks. It helps in improving the scalability and controllability of information networks.

Although there are lessons learned from practical experiments, simulation experiments, and mathematical analysis, interactions between layered network control methods is not fully explored. For example in [4], we verified that topology adaptation in an overlay network must operate on the control frequency which is higher than or at least as high as synchronization in physical sensor networks. Analysis of layered model from an interdisciplinary viewpoint can be found in [5], which regards layered control as an optimization problem. In [6], we investigated the relationship among the degree of coupling and the resultant characteristics of layered adaptive routing mechanisms. In the evaluation, we considered interactions between routing in an overlay network and routing in a mobile ad-hoc network. An overlay network consists of some of physical nodes of the mobile ad-hoc network as communicating hosts and virtual links corresponding to connections established among those nodes. Simulation results indicated that the coupling where the upper-layer routing mechanism took the performance of the lower-layer routing mechanism

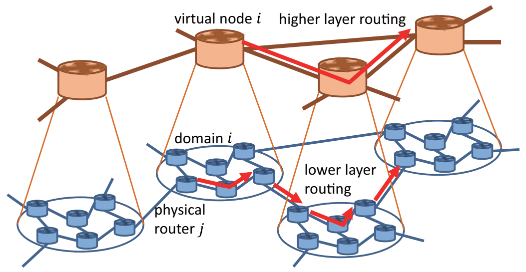

Figure 1: Layered network

into account led to the smallest end-to-end delay and the small delay variation.

In this paper, we analyze another scenario of inter-layer interactions. As the higher-layer control, we consider routing in the higher-layer network, which consists of virtual nodes and physical links among them. A virtual node corresponds to a lower-layer network, e.g. AS, which consists of physical routers and physical links among them as shown in Fig. 1. As described above, a lower-layer network conducts intra-network routing to establish paths between an arbitrary pair of routers in the domain. Communication between physical routers belonging to different domains is performed over a path established across multiple domains which are selected by the higher-layer routing. We change the degree of coupling of two layers and evaluate the time constant, the convergence time, and the path length.

2. Attractor Selection Model

A routing protocol adopted in this paper is developed based on a nonlinear mathematical model of biological behavior. The model, called the attractor selection model, was derived from autonomous and adaptive nutrient synthesis of *E. coli* in order to live and grow in the dynamically changing nutrient condition of the environment [7]. There is not 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 is formulated in the form of a Langevin type of equation.

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

$\vec{x}$ 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 correspond 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.

The attractor selection model is expected to explain adaptive behavior of biological systems other than bacterial nutrient synthesis. For example, perception of an ambiguous figure switches between multi-stable patterns in the human brain [8]. Watching, e.g. "My Wife and My Mother-in-Law", the brain perceives it as either of a young woman or an aged woman. That is, perception moves between two attractors in the language of the attractor selection model. The higher-tier perception of the whole image is influence by lower-tier perception of individual ambiguous parts, e.g. a chin of a young woman or a nose of an aged woman, similarly to a binding process [9]. Perceptions of individual parts are independent from each other at the beginning and they fluctuate between potential patterns or attractors. At this time, the higher-tier perception is unstable. Once perceptions of some parts eventually become consistent with each other, it triggers convergence of higher-tier perception to one of stable patterns. It further drives unstable perceptions of other parts to those patterns that are consistent with the global pattern and makes them stable. Behavior of layered routing mechanisms introduced in the next section is similar to the above perception process and we expect that our evaluation gives insight into perception of ambiguous figures.

3. Layered Adaptive Routing

The original model of our attractor selection-based routing mechanism is presented in [10]. In an attractor selection-based routing mechanism, attractors correspond to next-hop nodes to forward a packet.

Virtual node i corresponding to domain i maintains state vector $\vec{x}_{i,s}$ for destination virtual node s corresponding to domain s. It is defined as $\vec{x}_{i,s} = \{x_{i,s,1}, x_{i,s,2}, \ldots, x_{i,s,n}\}$ where n is the number of neighbor nodes. At regular control intervals, each virtual node i updates state vectors $\vec{x}_{i,s}$ for all destination nodes s by using the following equation.

$$\frac{d\vec{x}_{i,s}}{dt} = \vec{f}_1(\vec{x}_{i,s}) \times \alpha_{i,s} + \vec{\eta} \qquad (2)$$

$\vec{f}_1(\vec{x}_{i,s})$ defines n attractors where one vector element $x_{i,s,j}$, $(1 \leq j \leq n)$ of state vector $\vec{x}_{i,s}$ has a large value and the others have a small value. In packet forwarding, a neighbor node with the largest vector element is chosen as a next hop for destination virtual node. $\alpha_{i,s}$ is the activity of the current path from virtual node i to virtual node s, which is given as the ratio of the hop count of the current path in the higher-layer network to the minimum hop counts in the last 10 control intervals.

Similarly, physical router j in domain i maintains state vector $\vec{y}_{i,j,k}$ for destination physical router k in the same domain. At regular control intervals, each physical router j updates state vectors $\vec{y}_{i,j,k}$ for all destination routers k by using the following equation.

$$\frac{d\vec{y}_{i,j,k}}{dt} = \vec{f}_2(\vec{y}_{i,j,k}) \times \alpha_{i,j,k} + \vec{\eta} \qquad (3)$$

As $\vec{f_2}(\vec{y}_{i,j,k})$, we use the similar function to $\vec{f_1}(\vec{x}_{i,s})$. $\alpha_{i,j,k}$ is the activity of the current path from physical router j to physical router k in domain i, which is given as the ratio of the physical hop count of the current path in the domain to the minimum hop counts in the last 10 control intervals.

We consider four alternatives of coupling of two layers. The first one is *Independent*. The higher-layer routing uses Eq. (2) and the lower-layer routing uses Eq. (3). Each layer tries to maximize its own activity by establishing shortest paths independently from the other layer.

The second is *VNusePN*, where the higher-layer routing takes into account the activity of the lower-layer routing. In VNusePN, a virtual node uses the following equation in updating state vectors in place of Eq. (2).

$$\frac{d\vec{x}_{i,s}}{dt} = \vec{f_1}(\vec{x}_{i,s}) \times \alpha_{i,s} \times g_1(\alpha_{i,\cdot,\cdot}) + \vec{\eta} \quad (4)$$

$g_1(\alpha_{i,\cdot,\cdot})$ is a coupling function for a virtual node in the higher layer to reflect the performance of intra-domain routing. Among alternatives of coupling functions, we use $g_1(\alpha_{i,\cdot,\cdot}) = \sum_j(\sum_k \alpha_{i,j,k}/|N_i - \{j\}|)/|N_i|$, where N_i is a set of physical routers in domain i. That is, $g_1(\alpha_{i,\cdot,\cdot})$ gives an average of activities of physical routers in domain i, which virtual node i represents.

On the contrary, *PNuseVN* uses the following equation for a physical router to take into account the goodness of routing in the higher layer.

$$\frac{d\vec{y}_{i,j,k}}{dt} = \vec{f_2}(\vec{y}_{i,j,k}) \times \alpha_{i,j,k} \times g_2(\alpha_{i,\cdot}) + \vec{\eta} \quad (5)$$

$g_2(\alpha_{i,\cdot})$ is a coupling function for a physical router in the lower layer to reflect the performance of inter-domain routing. In this paper, we use $g_2(\alpha_{i,\cdot}) = \sum_s \alpha_{i,s}/|D - \{i\}|$, where D is a set of virtual nodes in a network.

Finally, *Both* is the tight coupling. Both of the higher-layer routing and the lower-layer routing try to maximize the total performance by sharing activities among layers by using Eqs. (4) and (5).

Intuitively speaking, the tight coupling, i.e. Both, leads to the best performance among the above four alternatives. However, it takes the longest to find the globally optimal solution and it is easily affected by slight perturbations.

4. Simulation Results

We built a network consisting of 10 domains with 30 nodes. Therefore, there were 10 virtual nodes. Their topologies were generated by the Waxman model [11]. We used NetLogo 5.0 and assumed no delay. We further assumed that a virtual node or a physical router had the up-to-date information about the length of all paths. We adopted the same parameters for routing mechanisms in both layers. We changed the ratio of control interval on the higher layer to that of the lower layer from 1 to 10 to see its influence.

We use the convergence time and the path length as performance measures. The convergence time is the number of time steps required for all nodes to achieve the activity of 1. At the beginning of a simulation run, all activities are 0 at all nodes and vector elements are set at random from 0 to 1. The path length is the average length of paths between arbitrary pair of physical routers in a network, which can be derived by multiplying the average path length of domains and the average path length in the higher layer. We also consider the time constant when 63.2% of nodes achieve the activity of 1 and the path length at the time constant. In the following, results averaged over 100 runs are depicted.

Figure 2 shows the average convergence time. As shown in the figure, the convergence time increases as the interval ratio becomes large. It is because the higher-layer routing takes longer time to converge for longer control intervals. The convergence times of Independent and VNusePN are smaller than those of PNuseVN and Both. Whereas the convergence time of PNuseVN approaches those of Independent and VNusePN, it remains high with Both as conjectured. In Fig. 3, the average path length is the shortest with Both and PNuseVN. We also note that the interval ratio does not affect the average path length very much.

As shown in Fig. 4, time constants of PNuseVN and Both increase in proportional to the interval ratio whereas they remain unchanged with Independent and VNusePN. It implies that lower layer routing is dominant in layered routing. However, as seen in Fig. 5, there is much room for improvement in terms of path length at the time constant. After the time constant the quality of paths is gradually improved with Independent and VNusePN. On the other hand, paths are as short as the converged ones at the time constant in the case of Both and PNuseVN with small interval ratios.

In conclusion, PNuseVN is the best coupling in the scenarios considered in the paper, whereas the difference with Both is not substantial. With PNuseVN, lower-layer routing takes into account the quality of paths in the higher-layer routing. As such, when the activity of the higher-layer routing becomes high, it induces convergence of lower-layer routing. The phenomenon is very similar to the perception process of ambiguous figures in the human brain and we need to investigate the implication in more detail.

5. Conclusion

In this paper, we investigated the influence of degree of coupling on the performance of layered routing mechanisms. Through simulation experiments we found that lower-layer routing was dominant in layered routing. The result that introduction of higher-layer awareness into lower-layer routing provides better performance conforms to the model of perception process of ambiguous figures in the human brain. We plan to further investigate the similarity and conduct additional experiments including resilience against failures and perturbations.

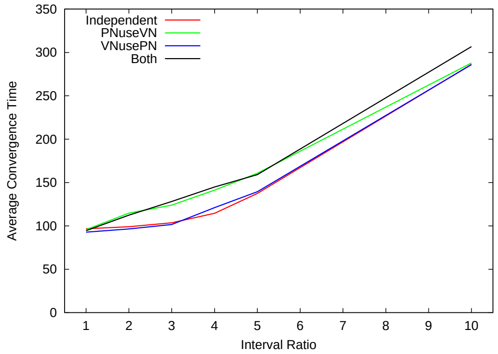

Figure 2: Average convergence time

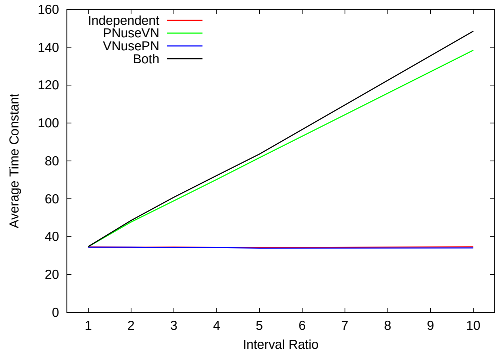

Figure 4: Average time constant

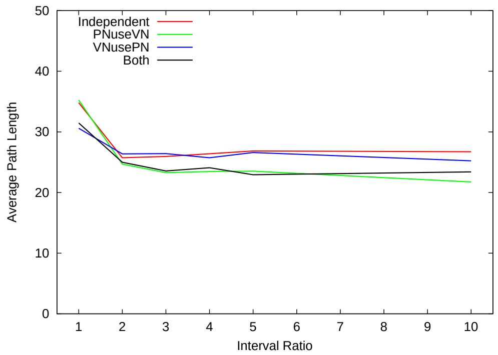

Figure 3: Average path length

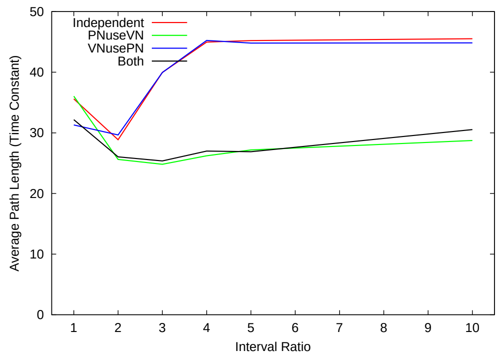

Figure 5: Average path length at time constant

Acknowledgment

This work is partly supported by Novel and innovative R&D making use of brain structures from the Ministry of Internal Affairs and Communications, Japan in FY2011.

References

[1] ITU-T, "Information technology - Open Systems Interconnection - Basic Reference Model: The basic model," ITU-T Recommendation X. 200, 1994.

[2] R. Jurdak, Wireless Ad Hoc and Sensor Networks: A Crosslayer Design Perspective, Springer-Verlag, 2007.

[3] L. D. Mendesa and J. J. Rodrigues, "A survey on crosslayer solutions for wireless sensor networks," Journal of Network and Computer Applications, vol. 34, no. 2, pp. 523–534, March 2011.

[4] N. Wakamiya and M. Murata, "Attractor composition-based self-adaptation in layered sensor-overlay networks," in Proceedings of NOLTA 2009, October 2009

[5] M. Chiang, S. H. Low, A. R. Calderbank, and J. C. Doyle, "Layering as optimization decomposition: A mathematical theory of network architectures," in Proceedings of the IEEE, vol. 95, no. 1, pp. 255–312, January 2007.

[6] N. Wakamiya and M. Murata, "Analysis of interaction between layered self-organizing network control," in Proceedings of NOLTA 2011, September 2011.

[7] A. Kashiwagi, I. Urabe, K. Kaneko, and T. Yomo, "Adaptive response of a gene network to environmental changes by fitness-induced attractor selection," PLoS ONE, vol. 1, no. 1, December 2006.

[8] J. Kornmeier and M. Bach, "Ambiguous figures - what happens in the brain when perception changes but not the stimulus," Frontiers in Human Neuroscience, vol. 6, no. 51, March 2012.

[9] C. Malsburg, "The Correlation Theory of Brain Function," Internal Report, Department of Neurobiology, Max-Planck-Institute for Biophysical Chemistry, 81-2, 1981.

[10] N. Asvarujanon, K. Leibnitz, N. Wakamiya, and M. Murata, "Robust and adaptive mobile ad hoc routing with attractor selection," in Proceedings of ADAMUS 2010, July 2010.

[11] B. M. Waxman, "Routing of multipoint connections," IEEE Journal on Selected Areas of Communications, vol. 6, no. 9, pp. 1617-1622, 1988.