Study on Interaction between Layered Self-Organization based Control

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ABSTRACT

Self-organization is considered one of key design principles to establish highly scalable, adaptive, and robust network systems to accommodate dynamic, diverse, and massive nodes and traffic. Although there are many proposals on self-organization based protocols that are useful, effective, and practical, there has never been any in-depth investigation into interaction, interference, and synergetic effects among multiple self-organization based control. In this paper, we show an idea of analysis of mutual interaction among layered self-organization based control. We consider an overlay network that is constructed over an ad-hoc network, both of which adopt adaptive routing protocols based on the attractor selection model, i.e. a mathematical model of adaptive behavior of biological systems. We modified the degree of coupling by changing the way how layered self-organization control shared an objective parameter. Through simulation experiments, we showed that lower layer-aware routing can provide the best performance, while coupling sometimes brings worse results than independent control.

Categories and Subject Descriptors

C.2 [**Computer Systems Organization**]: COMPUTER-COMMUNICATION NETWORKS

General Terms

Algorithms, Performance

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layered network control, self-organization, routing, adaptive control, attractor selection model

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1. INTRODUCTION

Today, billions of devices, such as PCs, mobile phones, and sensor nodes are connected to the Internet, to make our life safe, secure, and comfortable. The scale of the Internet continuously increases in the number, heterogeneity, and mobility of devices and many new applications are emerging with help of proliferation of networked devices. It implies that the current Internet is beyond control of conventional mechanisms and protocols, which were designed 30 years ago or added in an ad-hoc manner in response to emerging needs.

First, the growing scale prevents a centralized control mechanism from managing a network system as the whole, because collection of up-to-date information from all nodes consumes considerable amount of bandwidth, energy, and time. In addition, maintenance of global information must be performed frequently, in the same order as speed of change in topology and traffic demand. Even if centralized control is distributed to nodes, they still need to frequently communicate with each other to exchange their state information and to maintain the consistency among them. Secondly, most of current mechanisms and protocols adopt complicated rules with fine-tuned parameters to achieve the optimal performance and to react to dynamic changes such as failures and movement. It means that assumptions on operational environment, such as the number of nodes, diversity in traffic, mobility of nodes, and frequency and size of failures, are made in defining rules and setting parameters. As a result, a network system becomes prone to unexpected events and conditions, which are more likely to occur in a future network, and it easily collapses.

To address the problems, self-organizing control mechanisms, where each node autonomously decides its behavior based on local information it observes or obtains from neighbors and the global control emerges through mutual interaction among neighboring nodes, has been attracting researchers. Self-organization based networking is an interdisciplinary research field, since self-organizing phenomena are recognized in several research fields such as mathematics, physics, chemistry, social science, and biology. Among them, those researches inspired by self-organizing behavior of biological systems are most active and promising [3, 7]. Biological systems are inherently autonomous and self-organizing, where there is no centralized control unit dominating the whole, and they often exhibit scalable, adaptive, and robust properties. By being inspired by such biological systems, it is expected that network control mechanisms can achieve the scalability, adaptability, and robustness.

Although there are many successful bio-inspired self-organizing mechanisms, whose superiority to conventional mechanisms were verified through simulation and practical experiments, combination of multiple self-organizing mechanisms is not well-investigated. In [11], they analyzed combination of overlay routing and sleep scheduling in wireless sensor networks and showed that the speed of upper layer control should be as fast and faster than that of lower layer control. Analysis of layered model from an interdisciplinary viewpoint can be found in [2], but our focus in this paper is on the influence of interdependency among layered self-organizing routing on performance and stability.

In this paper, we show some preliminary results of our analysis on interaction between two layered self-organizing control mechanisms. More specifically, as a bio-inspired self-organizing control mechanism, we consider an attractor selection model-based routing [1] and as layering we consider an overlay network constructed over an ad-hoc network. The attractor selection model is a mathematical model which is derived from non-rule based adaptation of biological systems [5]. The attractor selection model has been applied to multi-path routing in overlay networks [6], clustering in wireless sensor networks [10], clustering in mobile ad-hoc networks [8], coverage control in wireless sensor networks [4] and so on. When layered routing protocols are tightly coupled with each other, a slight change in a path in one layer would easily and strongly affect the other. It leads to global optimization where both control reach the stable and optimal solutions in some cases, but it also results in instable routing where paths continuously fluctuate in both layers.

The rest of this paper is organized as follows. First in Section 2, we briefly introduce the attractor selection-based routing protocol. Next, we describe how overlay routing and ad-hoc routing are coupled with each other in Section 3. Then, in Section 4, we discuss preliminary results of our simulation experiments. Finally, we conclude the paper in Section 5.

2. BIO-INSPIRED ADAPTIVE ROUTING BASED ON ATTRACTOR SELECTION MODEL

In this paper, we consider interaction between routing protocols running on a wireless ad-hoc network and an overlay network, which is constructed over the ad-hoc network. As a routing protocol, nodes adopt the simplified version of MARAS [1], which is a routing protocol designed for mobile ad-hoc networks based on the attractor selection model.

2.1 Overview

MARAS is an on-demand routing protocol, where a path is established when it is required by a source node to send data messages to a designated destination node. Once a data message leaves a source node, it is forwarded among intermediate nodes toward the destination node. Each intermediate node selects a node to forward a data message from its neighboring nodes every time a data message arrives. For the purpose of selection of forwarding node, node i maintains a list of routing information. Routing information for destination node d is composed of variables of the attractor selection model, $\vec{m}_d = \{m_{d,j} | j \in N_i\}$ and α_d. $\vec{m}_d$ is called state vector, which is a vector of state values $m_{d,j}$ corresponding to the goodness of selection of neighboring node j for destination d. α_d is the activity, which expresses the goodness of the current path. Details of usage of them will be explained in the following sections. N_i corresponds to a set of neighboring nodes of node i.

2.2 Route establishment

At the beginning of communication, source node s looks up routing information corresponding to the intended destination node d in the list of routing information. If node s dose not have the routing information for destination node d, it generates a route request (RREQ) message and broadcasts it as in the case of AODV [9]. When a node receives a RREQ message destined for a node other than itself, it records its own ID on the RREQ message and broadcasts it. In this way, the RREQ message memorizes nodes that it has visited while being forwarded by broadcasting. When the number of forwarding reaches the maximum limitation determined in advance, the RREQ message is discarded. Since each RREQ message has a unique ID, duplicated RREQ messages are detected and discarded at an intermediate node.

When destination node d receives a RREQ message, the node generates a route reply (RREP) message and sends the message toward source node s by multi-hop unicast communication. A RREP message travels along the reverse path of the corresponding RREQ message. When a node including a source node receives a RREP message, it initializes routing information corresponding to destination node d. Regarding the state vector $\vec{m}_d$, the state value $m_{d,j}$ corresponding to the neighboring node j, from which it received the RREP message, is set at 10. In contrast, state values corresponding to the other nodes are set at 0. The activity α_d is set at 1.0, which means that the initial path is the current best. Finally, when the source node s receives a RREP message, it begins to send data messages.

2.3 Data message forwarding

When a node receives a data message destined for node d, it selects node j from its neighboring nodes as the next hop node according to the probability $\frac{m_{d,j}}{\Sigma_{k \in \bar{N}_i} m_{d,k}}$, and forwards the data message to node j. $\bar{N}_i$ corresponds to a set of neighboring nodes of node i except the node from which node i received the data message. If the node is only neighbor, the data message is discarded. A data message is forwarded by intermediate nodes while memorizing them until it reaches the destination node d or it is discarded by reaching the maximum number of forwarding.

2.4 Feedback and route maintenance

When destination node d receives a data message, it generates a feedback message and sends the message toward source node s. A feedback message is forwarded along the reverse path where the corresponding data message travelled, and eventually reaches node s.

When a node including a source node receives a feedback message at time t, it updates its routing information for node d. First, activity α_d is derived by the following equation.

$$\alpha_d = \frac{\min_{t-T<t' \leq t} w(t')}{w(t)} \quad (1)$$

where $w(t)$ corresponds to the travelled hop count of the

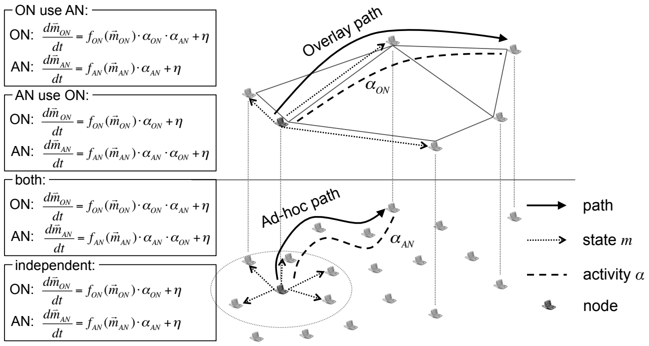

Figure 1: Layered routing based on attractor selection model.

feedback message from the destination node to the node itself received at time t, and T $(T > 0)$ is a parameter.

By using the new activity α_d, the node updates state vector $\vec{m}_d$ by the following equation.

$$\frac{dm_{d,j}}{dt} = \frac{\alpha_d(\beta\alpha_d^\gamma + 1/\sqrt{2})}{1 + m_{d,max}^2 - m_{d,j}^2} - \alpha_d m_{d,j} + (1 - \alpha_d)\eta_{d,j\in N_i} \tag{2}$$

where $m_{d,max} = \max_{k\in N_i} m_{d,k}$, and η_d is the Gaussian noise. β $(\beta > 0)$ and γ $(\gamma > 0)$ are parameters which control the influence of the activity on state values.

When the activity is high, a nonlinear dynamic system governed by Eq. 2 reaches an attractor, i.e. stable state, where one $m_{d,j}$ $(j \in N_i)$ has a high value and the other $m_{d,k}$ $(k \in N_i - \{j\})$ have a low value. It means that the current path is short enough and a node preferentially selects a certain node j forming the path as a next hop node. On the other hand, when the current path becomes inappropriate for node failure or link disconnection, the activity decreases. As a result, selection of next hop node will be driven by the third term of the right side of Eq. 2, i.e. noise. When a node occasionally selects a new good neighbor node, the activity eventually increases and it recovers preferential selection leading to the shortest path in the new condition. In summary, the attractor selection model is a kind of heuristics to find a state vector maximizing the activity, which is interpreted as the shortness of path in our routing.

In addition to feedback-based updating, the activity decays at intervals of τ $(\tau > 0)$ by the following equation and the state vector is updated by using the decayed activity accordingly, regardless of whether the node receives feedback messages in the preceding interval.

$$\alpha_d = \alpha_d - \delta \tag{3}$$

where δ $(\delta > 0)$ is a constant. When activity α_d becomes 0, the routing information corresponding to destination node d is removed from a list.

3. COUPLING LAYERED SELF-ORGANIZATION BASED ROUTING

In this paper, we consider a layered network model illustrated in Fig. 1. A lower layer is a wireless ad-hoc network, which consists of randomly distributed wireless ad-hoc nodes, and an overlay network, which is constructed on the ad-hoc network by appointing randomly chosen ad-hoc nodes as overlay nodes. The routing protocol explained in the previous section is adopted on both layers. A node which belongs to both of an overlay network and an ad-hoc network maintains two lists of routing information, i.e. a list of state vector $\vec{m}_{ON}$ and activity α_{ON} as an overlay node and a list of state vector $\vec{m}_{AN}$ and activity α_{AN} as an ad-hoc node. In the overlay network, the travelled hop count $w(t)$ is defined as the number of hops that a feedback message traversed from an ad-hoc node corresponding to an overlay destination node to the node itself in an ad-hoc network, i.e. physical hop count to the destination node. On the other hand, it is defined as the number of hops from a destination node of an ad-hoc path to the node itself.

Because of the structure, overlay routing and ad-hoc routing influence each other. When an overlay node intends to send data messages to another overlay node, it initiates routing procedures to find the shortest end-to-end overlay path in an overlay network. Since an overlay link is physically composed of ad-hoc nodes, it triggers ad-hoc routing to establish an ad-hoc path from an ad-hoc node corresponding to one end of an overlay link to an ad-hoc node corresponding to the other end of the overlay link. In an ad-hoc network, each node tries to establish and maintain the shortest path to a destination node, but a destination node dynamically changes due to stochastic selection of a next hop overlay node in overlay routing. When an overlay node changes a next hop node in an overlay network, it, as an ad-hoc node, also needs to establish or update an ad-hoc path to an ad-hoc node corresponding to the new next hop overlay node. If an ad-hoc path corresponding to a new overlay path is not stably established, the length of an ad-hoc path and the corresponding overlay link dynamically changes due to stochastic data message forwarding. As a result, the length of the end-to-end path from an overlay source node to an overlay destination node fluctuates and activity α_{ON} changes accordingly. If activity α_{ON} occasionally decreases, an overlay path changes and it further triggers reconstruction of ad-hoc paths. Such mutual interaction sometimes results in the shortest and stable path, but it possibly causes an unstable and fluctuating path.

To evaluate how interdependency among layered control affects performance and stability, we consider four alternatives of coupling which differ in the way of activity sharing.

- Independent: Each network tries to achieve their own goals, i.e. high activity and short path, while being influenced by behavior of the other layer implicitly. An overlay node updates its state vectors $\vec{m}_{ON}$ by using its own activity α_{ON} and an ad-hoc node updates its state vectors $\vec{m}_{AN}$ by using its own activity α_{AN}.

- Ad-hoc aware overlay routing (ONuseAN): An overlay network chooses an overlay path which improves the performance of ad-hoc routing, for example, by detouring a sparse area. An overlay node updates its state vectors $\vec{m}_{ON}$ by using the combined activity $\alpha_{ON} \times \alpha_{AN}$, and an ad-hoc node updates its state vectors $\vec{m}_{AN}$ by using its own activity α_{AN}.

- Overlay-aware ad-hoc routing (ANuseON): An ad-hoc network chooses a physical path connecting two overlay nodes, which leads to better overlay end-to-end

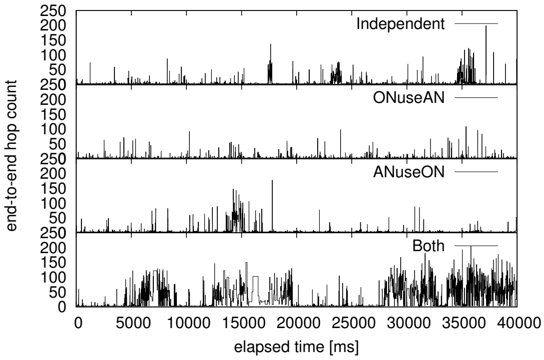

Figure 2: Temporal change of end-to-end hop count.

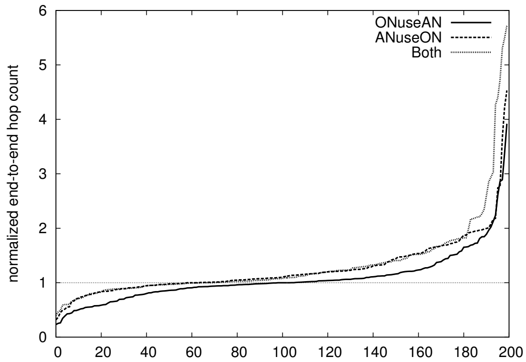

Figure 3: Normalized end-to-end hop count.

performance. An ad-hoc node, which also belongs to an overlay network, updates its state vectors $\vec{m}_{AN}$ by using the combined activity $\alpha_{AN} \times \alpha_{ON}$, and an overlay node updates its state vectors $\vec{m}_{ON}$ by using its own activity α_{ON}.

- Tight coupling (Both): Both of an overlay network and an ad-hoc network try to maximize the total performance by sharing the same goal. Both of an overlay node and an ad-hoc node, which also belong to an overlay network, update their state vectors $\vec{m}_{ON}$ and $\vec{m}_{AN}$ by using the combined activity $\alpha_{ON} \times \alpha_{AN}$.

Intuitively speaking, the tight coupling, such as “Both”, 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.

4. SIMULATION EXPERIMENTS

We arranged 150 immobile ad-hoc nodes in a 100×100 m area randomly and constructed an ad-hoc network. In the ad-hoc network, each node could communicate with any nodes within the communication range of 20 m. We assumed the ideal communication environment where there were no delay and no loss of messages. Randomly chosen 20 ad-hoc nodes were appointed as overlay nodes. They belonged to both of an ad-hoc network and an overlay network. An overlay network was constructed by establishing 50 overlay links between randomly chosen pairs of overlay nodes. In each of simulation experiments, we randomly chose a pair of a source node and a destination node from overlay nodes. Then, the source node generated data messages at regular intervals of 0.1 s and sent it toward the destination node for 400 s. We set $\beta = 10$, $\gamma = 5$, $\delta = 0.1$, $T = 5\ s$ and $\tau = 1\ s$, respectively, and the same setting was used in both of overlay routing and ad-hoc routing. At the beginning of a simulation run, all of ad-hoc and overlay nodes did not have any route information. We generated 200 random topologies and evaluated four alternatives of coupling on each of the topologies.

First in Fig. 2, we show an example of time series of the end-to-end hop count of four alternatives on the same topology. In the figure, the end-to-end hop count fluctuates over the whole simulation time due to stochastic selection of a forwarding node in an attractor selection model-based routing, i.e. MARAS, and implicit or explicit interaction among layers.

Next, a summary of simulation results is shown in Fig. 3. The y-axis corresponds to the normalized end-to-end hop count. The normalized end-to-end hop count is the number of hops from a source node to a final destination node in an ad-hoc network averaged over the whole simulation time and further normalized by the averaged end-to-end physical hop count of the case of “Independent” on the same topology. Results of 200 topologies are arranged along the x-axis in the ascending order of the normalized end-to-end delay. Note that results of three alternatives on the same value of x-axis are not necessarily the results for the same topology. From the figure, it can be seen that the coupling of “ONuseAN”, where an overlay node takes into account the activity of an ad-hoc network in derivation of a state vector, i.e. selection probability of next hop node, results in the shortest path in comparison with “ANuseON” and “Both”. The reason for this is as follows. The activity α_{ON} of an overlay node is derived from the total number of hops from the node to a destination node. Therefore, a slight change in ad-hoc paths does not affect α_{ON} very much. When an ad-hoc network cannot easily find and converge to the shortest path, it affects the activity α_{AN} of an ad-hoc node more than the activity α_{ON} of an overlay network. When ad-hoc routing and overlay routing are independent, an overlay network would keep the current path while an ad-hoc network struggles to find a good path. In “ONuseAN”, since an overlay network takes into account the activity α_{AN}, a decrease in α_{AN} triggers rerouting in an overlay network, to find a better overlay link leading to a shorter and more stable ad-hoc path. As a result, “ONuseAN” can achieve a shorter end-to-end path than the other couplings. However, compared with “Independent”, even “ONuseAN” has a longer path on about one third of topologies, while paths are shorter on more than one third of topologies. In the worst case, the established path is four times as long as that of “Independent”. In “ONuseAN”, overlay routing is directly affected by the goodness of ad-hoc routing. Therefore, when an ad-hoc path corresponding to a single overlay link occasionally becomes long, an overlay node corresponding to a source node of the ad-hoc path

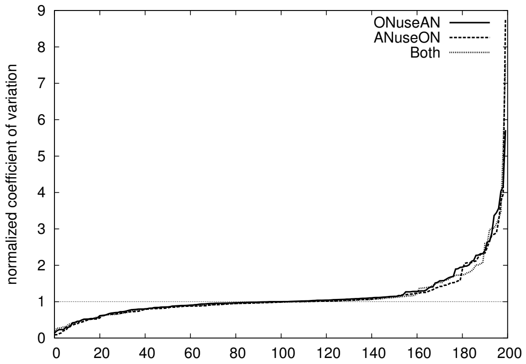

Figure 4: Normalized coefficient of variation of end-to-end hop count.

changes a next hop node stochastically. It results in a change in the further overlay path from the node to an overlay destination node, even if those overlay links constituting the path successfully converged to the optimal ad-hoc paths. In a sense, "ONuseAN" introduces stronger interference among ad-hoc paths constituting different overlay links than other couplings and ad-hoc paths disturb convergence each other.

Then, to analyze the stability of path, Fig. 4 summarizes results of the normalized coefficient of variation. The normalized coefficient of variation is derived by normalizing the coefficient of variation of established path in a simulation run by the result of "Independent" on the same topology. As shown in the figure, independently of coupling, the normalized coefficient of variation is almost the same. On about two third of topologies, an established path is as stable as or more than "Independent". However, on the remaining one third of topologies, a path fluctuates very much by introducing of coupling relationship. As explained in the above, sharing activities between layers strengthen interdependency not only between layers but also among paths in the same layer. As a result of mutual interference, global convergence is often disturbed and the established end-to-end path fluctuates.

5. CONCLUSION

In this paper, to investigate mutual interaction among layered self-organization based control, we consider an overlay network constructed on an ad-hoc network both of which adopt an attractor selection model-based routing mechanism. We evaluated the influence of different degree of coupling by changing the way how layered control share an objective parameter, i.e. the activity. Through simulation experiments, we showed that lower layer-aware routing can provide the best performance in the end-to-end delay to some extent.

Since only preliminary evaluation is conducted in the paper, we plan to investigate mutual interaction among layered self-organization based controls in more realistic scenarios where a topology dynamically changes and messages are lost by collision. In addition, we are going to consider combinations of other self-organizing protocols such as clustering and scheduling.

6. ACKNOWLEDGMENTS

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