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Attractor Composition-based Self-Adaptation in Layered Sensor-Overlay Networks

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Abstract—A new generation network needs to accommodate enormous numbers of nodes with high diversity and a wide variety of traffic and applications. To achieve higher scalability, adaptability, and robustness than ever before, we consider a new network architecture where all entities behave in a self-organizing manner based on biologically-inspired nonlinear mathematical models. In this paper, we show an example of layered self-adaptation of overlay/sensor networks adopting the attractor composition model. Simulation results demonstrate potential benefits of our approach.

1. Introduction

In the near future, a considerable number of sensing, computing, controlling, or other information devices will be placed, distributed, and embedded within our environment. They are interconnected and organize themselves as networks to cooperate with each other in order to provide information services appropriate for the context, i.e. time, condition of surroundings, and user's demand. In such ambient information environment, a network would often face unexpected or unpredictable user behavior, usage of network, and traffic patterns, which were not anticipated at the time the network was designed or built. Then, it collapses. The conventional network design methodology and architecture, where structures, functionalities, algorithms, and control parameters are designed and dimensioned to achieve their performance based on assumptions on the operating environment and relying on the prepared seems no longer feasible for new generation networks.

To tackle the problem, in [1] we proposed a framework for a new network architecture, which was more scalable to the number of connected nodes and the size of the network, more adaptive to a wide variety of traffic patterns and their dynamic change, and more robust to expected and unexpected failures independently of their magnitude and duration. Our fundamental paradigm is to perform organization and control of the whole network system in a distributed and self-organizing manner. In self-organizing control, each entity, e.g. node and network, decides its behavior based on local information obtained through observations and communication with neighboring entities. Through direct and/or indirect mutual interaction among entities, global control emerges to provide users and applications with appropriate network services.

Our scheme to establish the self-organizing network architecture is to adopt bio-inspired nonlinear mathematical models to network control. Biological systems are inherently fully-distributed and autonomous and they are known to exhibit self-organizing behavior. *Swarm intelligence* is a typical example of self-organization [2]. A group of social insects such as ants, termites, and honey bees often shows sophisticated and globally organized behavior, e.g. ant trail, cemetery formation, brood sorting, and division of labor, which is beyond mere collection of simple behavior of individuals. Such collective intelligence emerges from mutual and local interaction among simple agents.

In this paper, we first introduce biological nonlinear models, i.e. attractor selection and attractor composition in section 2 and then show an example of layered control mechanisms adopting an attractor compotision model in section 3. As a targeted application, we consider data gathering, where an overlay network built over wireless sensor networks collects sensor data from sensor nodes to a data-collecting node. Overlay and sensor networks adaptively self-organize logical and physical topologies to minimize the data gathering delay in a cooperative manner. In section 4, we show some preliminary results of layered adaptive control. Finally section 5 summarizes the paper.

2. Bio-inspired Nonlinear Models and Application to Network Control

The attractor selection model describes non-rule driven adaptation of *E. coli* cells to dynamically changing nutrient conditions in the living environment [3]. A mutant *E. coli* cell has a metabolic network consisting of two mutually inhibitory operons, i.e. chemical reactions, each of which synthesizes different nutrients. A general formula for dynamics of the concentrations of mRNA in cell i is,

$$\frac{d\vec{x}_i}{dt} = f(\vec{x}_i) \times \alpha_i + \vec{\eta}_i, \tag{1}$$

where $\vec{x}_i$ corresponds to the vector of concentrations of mRNA. $f(\vec{x}_i)$ is a function for chemical reaction in the metabolic network. α_i represents the cellular activity such as growth rate and expresses the goodness of the current

behavior, i.e. gene expression. $\vec{\eta}_i$ expresses internal and external noise affecting the cell's behavior. When the current mRNA concentrations are appropriate for the environmental nutrient condition, a cell can grow well and activity α_i becomes high. Consequently, the first term of Eq. (1) becomes dominant and function $f(\vec{x}_i)$ controls the behavior of cell. When the nutrient condition changes, activity α_i decreases and the relative influence of the noise term $\vec{\eta}_i$ becomes dominant. Then, the mRNA concentrations adaptively change to fit to the new condition. Applying this model to network control, $\vec{x}_i$ represents setting of control parameters or control policies and activity α_i, a scalar metric reflects the goodness of the control, e.g. throughput or delay. The attractor selection model has been applied to multipath routing in overlay networks [4] and adaptive routing in mobile ad-hoc networks [5], where communication is often affected by the unpredictable dynamic behavior of other sessions and mobility of nodes.

The attractor selection model describes adaptive behavior of a single entity. However, there are multiple entities in the same shared environment in an actual situation, such as *E. coli* cells in a reactor. In the attractor composition model, entities share the same activity as being formulated as,

$$\frac{d\vec{x}_i}{dt} = f(\vec{x}_i) \times \alpha + \vec{\eta}_i. \tag{2}$$

With such coupling, entities can cooperatively optimize the system, but behavior of an entity directly affects others and the system could be driven to the unstable condition.

3. Self-Organization Mechnisms in Layered Sensor-Overlay Networks

In this section, we first explain an application scenario and then self-organization mechanisms based on the attractor composition model will be proposed.

3.1. Layered Sensor-Overlay Network

We consider that heterogeneous sensor nodes having different sensing devices are deployed in the monitored region. An application running over wireless sensor networks periofically collects sensor data from several sensor nodes, called source nodes, to a sensor node, called a sink node, at certain data gathering intervals. Each of data gathering attempts is called round. A sink node, source nodes, and the data gathering interval are chosen based on application requirements without taking into account characteristics of underlying wireless sensor networks such as topology.

To save energy consumption and prolong the lifetime of wireless sensor networks, sensor nodes usually adopt sleep control. They wake up, obtain sensory information and/or receive messages from neighbors, deposit the obtained data in a local buffer or send it to a neighbor node toward a destination, and then go back to a sleep mode at regular operational intervals. Therefore, a message can be transmitted

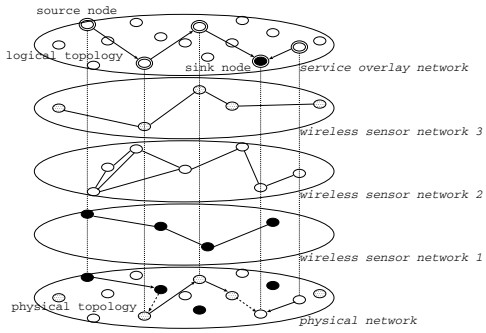


Figure 1: Layered sensor-overlay network

from a sensor node to a neighbor only when both sender and receiver are awake at the same time. For the sake of simplicity, in this paper we assume that sensor nodes of the same intrinsic operational interval are synchronized and they move between sleep and active states at the same time.

Furthermore, We assume that a message travels from a sensor node to a destination node on the shortest path in terms of the number of hops, but the path contains only sensor nodes which synchronize with each other except for the last hop. If a sensor node has a destination node as a neighbor, it directly sends a message to the neighboring destination when both wake up at the same time.

An image of layered sensor-overlay network is illustrated in Fig. 1, where different colors correspond to different intrinsic operational intervals. Arrows in the bottom network constitute physical paths from source nodes to a sink node. Solid arrows corresponds to message transmission between sensor nodes with the same operational interval and dashed arrows corrsponds to message transmission that causes buffering delay.

3.2. Activity definition

In this paper, we use the average data gathering delay, i.e. the average time required for messages to reach a sink node per round, to define the activity. Both of overlay and sensor networks dynamically adapt the topology to minimize the data gathering delay. The dynamics of activity is given as,

$$\frac{d\alpha}{dt} = \rho(\frac{d_{min}}{d_{avg}} - \alpha). \tag{3}$$

The initial vale is set at 0.5. When messages are received from all source nodes for round k, the per-round average data gathering delay $d(k)$ is calculated. Then, the average data gathering delay d_{avg} is derived as an average of $d(k)$ of the latest W_{round} rounds, that is, $d_{avg} = \sum_{i=k-W_{round}+1}^{k} d(i)/W_{round}$. d_{min} is the minimum of d_{min} for the latest W_{round} rounds. ρ $(0 < \rho < 1)$ is a parameter which determines the speed of adaptation. A large ρ makes a system too sensitive to instantaneous fluctuation and the topology does not become stable. On the other hand, with too small ρ, it takes long time to find a good topology.

3.3. Self-adaptation in Overlay Network

A logical overlay network consisting of a sink node and several source nodes can take any topology such as star, tree, clustered, and mesh. In general, it is not trivial for an application to choose the optimal topology without information about the physical network topology. However, the attractor selection model enables an overlay network to adaptively choose the better or best logical topology.

Following our previous work [5], given N as the number of topologies that an overlay network has as alternatives, we formulate the dynamics of state value x_i of topology i $(1 \leq i \leq N)$, which gives the preference of topology i, as,

$$\frac{dx_i}{dt} = \frac{\alpha(\beta\alpha^\gamma + \frac{1}{\sqrt{2}})}{1 + \max x_j^2 - x_i^2} - \alpha x_i + \eta_i. \quad (4)$$

Initially, state values are all set at zero. At each adaptation timing, an overlay network evaluates the state vector and chooses the topology with the largest state value. This function has stable attractors having one high state value and the others low state values, such as state vector $\vec{x} = (x_1, \ldots, x_i, \ldots, x_N) = (H, L, \ldots, L)$ and $(L, \ldots, H, \ldots, L)$, at the equilibrium. β and γ are parameters which define values H and L. η_i is the white Gaussian noise with zero mean and variance σ.

3.4. Self-adaptation in Wireless Sensor Network

Heterogeneous sensor nodes have different intrinsic operational intervals depending on their application and device, e.g. several seconds for location-aware services, several minutes for light and temperature control, and several hours for environmental monitoring. Although accommodating all nodes in a single network allows a message to move from a source node to a sink node with the smallest delay, it is only the waste of energy to force nodes of an hourly operational interval to operate every other second all the time. Therefore, we need a mechanism for heterogeneous wireless sensor networks to be dynamically connected, merged, and seperated if necessary and beneficial.

In our proposal, based on the attractor composition model, sensor nodes dynamically and adaptively decide whether to synchronize with other operational intervals based on the activity. Attractors in this case correspond to operational intervals to synchronize with. Similarly to the overlay network adaptation, the dynamics of state value y_i of operational interval i $(1 \leq i \leq M)$ among M operational intervals is formulated as,

$$\frac{dy_i}{dt} = \frac{\alpha(\beta\alpha^\gamma + \frac{1}{\sqrt{2}})}{1 + \max y_j^2 - y_i^2} - \alpha y_i + \eta_i, \quad (5)$$

At each adaptation timing, a sensor node evaluates the state vector and chooses an operational interval with the largest state value to synchronize with in addition to its intrinsic operational interval. If the intrinsic operational interval has the largest state value, a sensor node operates only on the intrinsic operational interval.

4. Simulation Results and Discussion

In this section, we show some simulation results and discuss the behavior of layered adaptive control.

4.1. Simulation Setting

We randomly distributed 150 sensor nodes in 200×200 square meter region and the wireless communication range was set at 25 meters. Intrinsic operational interval of each sensor was randomly chosen among 5, 10, and 15 minutes. We eliminated node layouts in which sensor nodes of the same group could not form a connected network.

An overlay network consisted of one randomly chosen sink node and four randomly chosen source nodes. Among all 256 logical topologies which could be constructed among five nodes, only those physically connected, on average about 100, were considered as alternatives. The data gathering interval was set at 10 minutes. Through a simulation run, there was only one overlay network.

We compare four different scenarios, i.e. *Static*, *ON*, *WSN*, and *ON+WSN*, depending on whether adaptive control is performed or not. As parameters of the attractor selection, β and γ are set at 50 and 3 respectively [5]. The adaptation rate ρ and the noise intensity σ were set at 0.1 and 0.01 respectively. We set W_{round} at 10. Averaged values of 100 runs of 10000 minutes are shown.

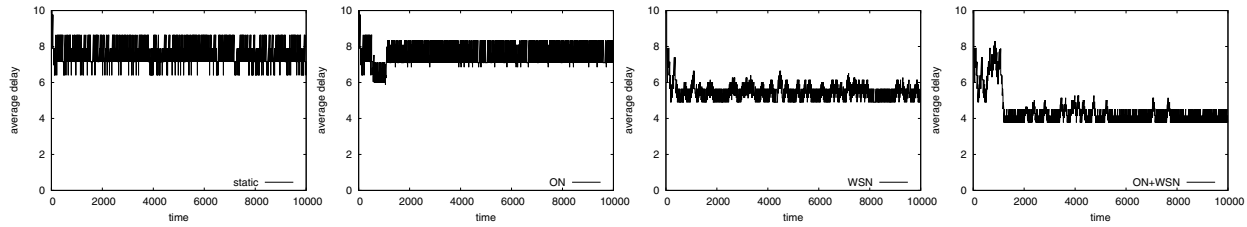
4.2. Simulation Results

First, we show the transient behavior of layered adaptation control in Figs. 2 through 4, where the adaptation interval of overlay network, denoted as I_{ON} is 500 minutes, and that of wireless sensor networks I_{WSN} ranges from 50 to 150 minutes. The figures are generated from one set of simulation runs, where the same random seed was used in all four scenarios.

In Fig. 2, the average data gathering delay d_{avg} fluctuates even in the case of Static. This is because that the data gathering interval is determined independently from operational intervals of sensor nodes. Messages are sometimes forced to wait until both of a sensor node holding the message and a receiver node wake up at the same time. In some cases, multiple messages are sent at once due to buffering.

Although ON alone cannot effectively decrease the delay, ON+WSN leads to the minimum delay as a combination in Fig. 2. In the case of ON and ON+WSN, an overlay network looks for and finds a logical topology leading to the smaller delay as shown in Fig. 3 where y-axis shows an identifier of logical topology. In both cases, an overlay network stays at a certain attractor after about 1000 minutes. The activity reaches sufficiently high level to keep the system stable with small perturbation as shown in Fig. 4.

Next, we investigate the mutual effect of the adaptation intervals. Intuitively, the adaptation interval of wireless sensor networks must be larger than the data gathering interval and smaller than that of an overlay network, so that



(a) Static (b) ON (c) WSN (d) ON+WSN

Figure 2: Average data gathering delay

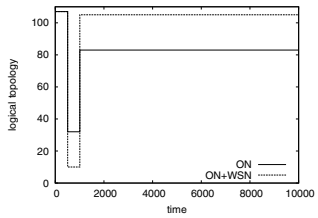
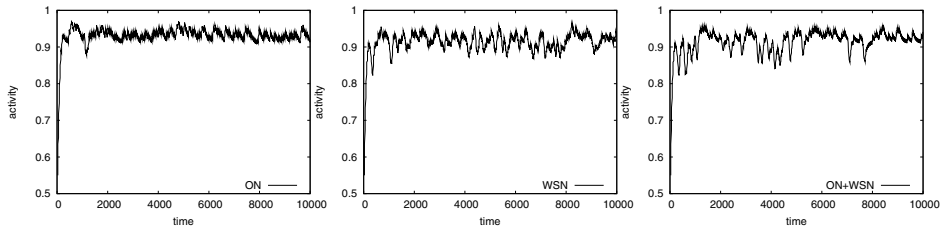


Figure 3: Logical topology



(a) ON (b) WSN (c) WSN+ON

Figure 4: Activity

Table 1: Influence of adaptation intervals

I_{WSN}		I_{ON}		
		10 min	100 min	500 min
5–15 min	avg	3.89	3.42	3.46
	var	0.58	0.64	0.62
50–150 min	avg	3.62	3.41	3.39
	var	1.30	1.32	1.60
250–750 min	avg	3.54	3.65	3.32
	var	2.70	3.25	3.47

each network can evaluate the goodness of attractor.

Results of evaluation of various combinations of I_{ON} and I_{WSN} are summarized in Table 1. Table 1 indicates that the best combination of adaptation intervals is I_{ON}=500 minutes and I_{WSN}=250–750 minutes in regard to the average data gathering delay. Another finding is that the larger adaptation interval especially in wireless sensor networks lead to larger fluctuation in the average data gathering delay. A reason for this is that, with late and intermittent adaptation, sensor nodes abruptly change their synchronization reacting major changes in the data gathering delay caused by previous adaptation. We will investigate their mutual effect in more detail as the next step of research.

5. Conclusion

In this paper, we proposed layered self-adaptation control based on the attractor composition model and evaluated the performance and mutual effect. We furtner need to investigate detailed behavior of mutual interaction and then we plan to evaluate the robustness, adaptability, and stability of the layered adaptation. We believe that a small-scale disruption can be hidden from an upper layer by local adaptation in a lower layer by layered adaptation control, which leads to high robustness and stability.

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